Essays on Vulnerability, Finance and Livelihoods of Rural Households in Southeast Asia

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Zusammenfassung

Südostasien, eine der dynamischsten Wirtschaftsregionen der letzten Jahrzehnte. Länder wie Kambodscha, Laos, Thailand und Vietnam verzeichnen dabei ein signifikantes Wirtschaftswachstum und bemerkenswerte Erfolge bei der Armutsbekämpfung. Dennoch stehen diese Länder noch vor den verschiedensten Herausforderungen, wie eine wachsende Ungleichheit, einem abnehmenden Wachstum der landwirtschaftlichen Produktivität sowie der Zerstörung der natürlichen Ressourcen. Ländliche Haushalte in diesen Ländern, deren Einkommen weitgehend von der landwirtschaftlichen Produktion und der Extraktion natürlicher Ressourcen abhängt, sind in hohem Maße verschiedenen Arten von Schocks ausgesetzt, wie z. B. extremen Wetterereignissen, Marktinstabilität oder Krankheiten. Da die Sozialversicherungsmechanismen in diesen Ländern noch unterentwickelt sind, kann das Auftreten von Schocks schwerwiegende Auswirkungen auf die Wohlfahrt und die Lebensgrundlage der Haushalte haben. Dies kann dazu führen, dass sie möglicherweise in einen Kreislauf von Armut und Ernährungsunsicherheit gefangen werden. Daher ist ein besseres Verständnis über die Vulnerabilität und Resilienz von Haushalten gegenüber Schocks unerlässlich, um Entscheidungsträgern und Praktikern wertvolle Informationen für die Gestaltung effektiver Programme zum Schutz vulnerabler Bevölkerungsgruppen zu liefern.

Kredite sind eine wichtige Finanzierungsquelle für Haushalte, da sie finanzielle Engpässe lindern, die ihnen den Zugang zu Märkten, Technologien oder die Erfüllung ihrer dringenden Bedürfnisse für Produktion und Konsum während Notlagen verwehren. Die empirische Evidenz über die Auswirkungen von Krediten auf die Wohlfahrt der Haushalte, auf Ungleichheit und ihre Rolle bei der Verminderung der Auswirkungen von Schocks bleibt jedoch uneindeutig. Einerseits zeigen einige Studien, dass der Zugang zu Krediten die Arbeitsproduktivität steigert, die Wohlfahrt der Haushalte erhöhen und Armut reduzieren kann.

Außerdem ermutigt er risikoaverse Landwirte, ihre Produktionsaktivitäten auszuweiten und produktive Strategien für den Lebensunterhalt zu verfolgen. Andererseits können Kredite dazu führen, dass Haushalte in Überschuldung oder Zahlungsunfähigkeit geraten und so ihren Wohlstand unterminieren. Darüber hinaus sind wachsende Ungleichheit und soziale Instabilität mögliche, unbeabsichtigte Folgen, wenn die Vorteile des Kreditmarktes nicht proportional über die Bevölkerungsgruppen verteilt sind.

Basierend auf Datensätzen auf Haushaltsebene besteht diese Arbeit aus fünf Forschungsarbeiten, die darauf abzielen, (i) die Vulnerabilität und Resilienz von Haushalten gegenüber Schocks zu bewerten, indem die Auswirkungen von Schocks auf verschiedene Indikatoren des Wohlbefindens von Haushalten und Coping-Strategien untersucht werden, (ii) die Rolle von Krediten bei der Milderung negativer Auswirkungen von Schocks und ihre Auswirkungen auf das Wohlbefinden und die Ungleichheit von Haushalten zu untersuchen und (iii) die Wechselbeziehung zwischen dem Vulnerabilitätskontext, den Vermögenswerten für den Lebensunterhalt sowie den Ergebnissen der landwirtschaftlichen Produktion und der Extraktion natürlicher Ressourcen zu analysieren.

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Die erste Forschungsarbeit mit dem Thema " Multiple shocks and household coping strategies in rural Cambodia " zielt darauf ab, die Auswirkungen von Schocks auf den Konsum und die Bildungsausgaben von Haushalten zu analysieren und untersucht, wie Haushalte auf Schocks reagieren. Die Ergebnisse zeigen, dass die Haushalte weniger gegen kovariate Schocks geschützt sind, insbesondere gegen Überschwemmungen, Dürren und Viehseuchen. Überschwemmungen wirken sich negativ auf den Gesamtkonsum der Haushalte sowie den Lebensmittelkonsum aus. In ähnlicher Weise verursachen Viehseuchen einen Rückgang der Bildungsausgaben der Haushalte. Sie zwingen die Haushalte diese zu bewältigen indem sie langlebige Vermögenswerte verkaufen und natürliche Ressourcen abbauen. Obwohl Dürren den Konsum der Haushalte nicht signifikant beeinflussen, drängen sie Haushalte dazu, ihre Kinder zur Arbeit zu schicken, langlebige Besitzwerte zu verkaufen oder natürliche Ressourcen zu extrahieren. Im Gegensatz dazu scheinen Gesundheitsschocks keine signifikanten und negativen Auswirkungen auf den Haushaltskonsum zu haben. Als Reaktion auf diese Art von Schocks neigen Haushalte dazu, Strategien zur Risikoteilung zu nutzen, wie beispielsweise das Anleihen und das Erhalten von Unterstützung durch Freunde und Verwandte. Zusätzlich zu den Schocks haben einige Haushalts- und dorfspezifische Merkmale signifikante Auswirkungen auf die Coping-Strategien der Haushalte. Die Wahrscheinlichkeit Kinderarbeit als Coping-Strategie einzusetzen, ist positiv mit der Haushaltsgröße und dem Alter des Haushaltsvorstands verbunden. Haushalte, die größer sind und sich entfernt von Märkten befinden, verkaufen eher langlebige Besitzwerte, um Schocks zu entgegnen. Haushalte mit einem geringeren Anteil männlicher Erwachsener und einem höheren Anteil älterer Mitglieder und Mitgliedern mit nicht-landwirtschaftlichen Berufen sind weniger geneigt, natürliche Ressourcen zu extrahieren. Das Leben in einem Dorf mit besseren sozioökonomischen Bedingungen hält die Haushalte ebenfalls davon ab, sich an der Extraktion natürlicher Ressourcen zu beteiligen. Haushalte von ethnischen Minderheiten, mit älteren Haushaltsvorständen und einem höheren Anteil an älteren Mitgliedern haben seltener Zugang zu Krediten. Gleichzeitig erhalten Haushalte mit einem höheren Anteil an alten Mitgliedern tendenziell mehr Unterstützung von Freunden und Verwandten, während sie auf Schocks reagieren.

Die zweite Forschungsarbeit mit dem Thema "Credit and Ethnic Consumption Inequality in the Central Highland of Vietnam" zielt darauf ab, die Unterschiede im Zugang zu Krediten und deren Auswirkungen auf den Konsum der Haushalte sowie die Konsumungleichheit zwischen ethnischen Gruppen zu untersuchen. Die Ergebnisse zeigen, dass Haushalte aus der indigenen ethnischen Minderheit beim Zugang zu formellen Krediten stärker benachteiligt sind und mehr auf informelle Kredite angewiesen sind als Haushalte aus der ethnischen Mehrheit. Zudem sind sie mit einer höheren Besicherungsquote konfrontiert und die Höhe der formellen Kredite, die sie erhalten könnten, ist geringer. Der Einfluss von formellen Krediten auf den Konsum der mehrheitlichen Bevölkerung ist ebenfalls höher als der der einheimischen Minderheit, was zu einer signifikanten Zunahme der Konsumungleichheit zwischen den ethnischen Gruppen führt. Unsere Ergebnisse machen deutlich, dass Hilfsprogramme zur Unterstützung indigener Haushalte gefördert werden sollten, mit dem Ziel ihren Zugang zu formellen Krediten zu verbessern und die Effektivität dieser Kredite zu erhöhen.

Die dritte Forschungsarbeit mit dem Thema " Shocks, Credit and Production Efficiency of Rice Farmers in Vietnam" zielt darauf ab, (i) die Auswirkungen von Krediten und Schocks auf die Effizienz der Reisproduktion zu untersuchen und (ii) die Rolle von Krediten bei der Abmilderung der Auswirkungen von Schocks zu analysieren. Die Ergebnisse zeigen, dass extreme Wetterereignisse, Landfragmentierung und die Migration von Haushaltsmitgliedern die Hauptursachen für Ineffizienz darstellen. Der Viehbestand, die landwirtschaftliche Mechanisierung sowie Bildung stellen hingegen positive Faktoren für die Effizienz der Reisproduktion dar. Die Ergebnisse zeigen zudem, dass der Zugang zu Krediten eine signifikante Rolle bei der Abmilderung der negativen Auswirkungen von extremen Wetterereignissen spielt. Es wird vorgeschlagen, den Landwirten mehr Hilfe und Unterstützung bei der Abmilderung der schwerwiegenden Auswirkungen von extremen Wetterereignissen zu geben, insbesondere durch die Förderung von ländlichen Kreditmärkten. Darüber hinaus sollte der Förderung landwirtschaftlicher Mechanisierung, Land-Defragmentierung, Viehzucht und der Verbesserung der ländlichen Bildung eine hohe Priorität eingeräumt werden, um die Effizienz der Reisproduktion zu verbessern.

Die vierte Forschungsarbeit befasst sich mit "Shocks, Agricultural Productivity and Natural Resource Extraction in Southeast Asia". Die Forschung wird in vier südostasiatischen Ländern durchgeführt: Kambodscha, Laos, Thailand und Vietnam. Ziel ist dabei, den Einfluss der landwirtschaftlichen Produktivität und Schocks auf die Extraktion natürlicher Ressourcen durch ländliche Haushalte zu untersuchen. Die Ergebnisse zeigen, dass Wetter- und Marktschocks zu den Faktoren gehören, die Haushalte signifikant dazu bringen mehr natürliche Ressourcen zu extrahieren und das eine Steigerung der landwirtschaftlichen Produktivität der Extraktion natürlicher Ressourcen entgegenwirken könnte. Darüber hinaus zeigt sich, dass die Bildung der Haushalte, die Verfügbarkeit von Unternehmen und der Zugang zu Elektrizität im Dorf negativ mit der Entnahme natürlicher Ressourcen verbunden sind. Es wird empfohlen, Maßnahmen zur Steigerung der landwirtschaftlichen Produktivität zu priorisieren und den Landwirten mehr Hilfe und Unterstützung zukommen zu lassen, um die schweren Auswirkungen von Wetter- und Marktschocks abzumildern. Darüber hinaus sollten auch die Förderung der ländlichen Bildung, die Beschleunigung der ländlichen Elektrifizierung und die Unterstützung der Entwicklung lokaler Unternehmen umgesetzt werden.

Schlagworte: Südostasien, Vulnerabilität, Krediten

Summary

Located in Southeast Asia, one of the world's most dynamic economic regions in recent decades, Cambodia, Laos, Thailand, and Vietnam are experiencing significant economic growth and remarkable achievements in poverty reduction. However, these countries are still suffering from several challenges such as growing inequality, decreasing growth in agricultural productivity, and natural resource degradation. Besides, rural households in these countries, whose income largely depends on agricultural production and natural resource extraction, are highly exposed to different types of shocks such as weather shocks, market instability, or illnesses. As social insurance mechanisms in these countries are still underdeveloped, the occurrence of shocks might cause severe impacts on households' welfare and livelihoods, potentially trapping them in the vicious cycles of poverty and food insecurity. Therefore, improved insights into household vulnerability and resilience to shocks is essential to provide useful information for policymakers and practitioners to design effective programs for protecting the vulnerable population.

Credit is an important source of finance for households as it relieves financial constraints, which prevent them from accessing markets, technologies or fulfilling their urgent needs for production and consumption during the time of hardships. However, empirical evidence on the impact of credit on household welfare, on inequality, and their role in mitigating the impact of shocks remains ambiguous. On the one hand, some studies show that access to credit could significantly boost labor productivity, enhance household welfare and reduce poverty. It also encourages risk-averse farmers to expand their production activities and to pursue productive livelihood strategies. On the other hand, credit may cause households to fall into over-indebtedness or default, consequently undermining their well-being. Furthermore, growing

inequality and social instability are possible unintended consequences if benefits from the credit market are not proportionately distributed.

Based on household-level datasets, this thesis is composed of four research papers, aiming to (i) assess household vulnerability and resilience to shocks by examining the impact of shocks on different household well-being indicators and shock-coping strategies, (ii) investigate the role of credit in mitigating negative impacts of shocks, and its effects on household well-being and inequality, and to (iii) analyze the interrelationship between vulnerability context, livelihood assets, and outcomes of agricultural production and natural resource extraction.

The first paper on “Multiple shocks and household coping strategies in rural Cambodia” aims to analyze the impact of shocks on household consumption and education expenditure and to examine how households respond to shocks. The results show that households are less protected against covariate shocks, particularly floods, droughts, and livestock diseases. Floods negatively affect total household consumption and food consumption. Similarly, livestock diseases cause a decline in household education expenditure. They force households to cope by selling durable assets and extracting natural resources. Although droughts do not significantly affect household consumption, these shocks push households into sending their children to work, selling durable assets or extracting natural resources. In contrast, health shocks do not appear to have significant and negative effects on household consumption. In response to this type of shock, households tend to use risk-sharing strategies such as borrowing and receiving assistance from friends and relatives. In addition to shocks, some household and village characteristics also have significant effects on household shock-coping strategies. The likelihood of using child labor is positively associated with household size and age of household head. Households with larger household sizes and living far from markets are more likely to sell durable assets to cope with shocks. Households are less likely to extract natural resources if they have a lower share of male adults and a higher share of old members and non-farm occupations. Living in a village with better socioeconomic conditions also discourages households to participate in natural resource extraction. Ethnic minority households with older household heads and higher shares of old members are less likely to have access to credit. Meanwhile, households with a larger share of old members tend to receive more assistance from friends and relatives in response to shocks.

The second paper on “Credit and Ethnic Consumption Inequality in the Central Highland of Vietnam” aims to investigate the differences in access to credit and its impact on household consumption and consumption inequality between ethnic groups. Results show that households from the indigenous ethnic minority group face more disadvantages in accessing formal credit and rely more on informal credit than those from the ethnic majority. They also face a higher collateral ratio and the amount of formal loans they could access is lower. The impact of formal credit on the consumption of the majority is also higher than that of the indigenous minority, consequently causing a significant increase in consumption inequality between the ethnic groups. Our findings call for assistance programs to support indigenous households to improve their access to formal credit as well as to enhance the effectiveness of these loans.

The third paper on “Shocks, Credit and Production Efficiency of Rice Farmers in Vietnam” aims to (i) investigate the impact of credit and shocks on rice production efficiency, and to (ii) examine the role of credit in mitigating the impact of shocks. Results show that weather shocks, land fragmentation, and the migration of household members are the major sources of inefficiency. Meanwhile, livestock, farm mechanization, and education are positively affecting rice production efficiency. The findings also indicate that access to credit plays a significant role in mitigating the negative impact of weather shocks. More assistance and support to farmers in mitigating the severe effect of weather shocks, in particular, via the promotion of rural credit markets is suggested. In addition, encouraging farm mechanization, land defragmentation, livestock farming, and the improvement of rural education should be given a high priority to improve rice production efficiency.

The fourth paper is on "Shocks, Agricultural Productivity and Natural Resource Extraction in Southeast Asia". It is conducted in four Southeast Asian countries, including Cambodia, Laos, Thailand and Vietnam. The objective of this paper is to investigate the impact of agricultural productivity and shocks on natural resource extraction by rural households. Findings show that weather shocks and market shocks are among the factors that significantly push households to extract more natural resources and enhancing agricultural productivity could discourage natural resource extraction. In addition, it shows that household education, the availability of enterprises, and access to electricity in the village are negatively associated with natural resource extraction. It is recommended that measures for enhancing agricultural productivity be prioritized and more assistance and support to farmers for mitigating the severe effect of weather shocks and market shocks be provided. Furthermore, promoting rural education, accelerating rural electrification, and supporting the development of local enterprises should also be implemented.

Keywords: Southeast Asia, Credit, Vulnerabiltiy

Table of Contents

List of Abbreviations

ADB	Asian Development Bank
CMP	Conditional-Mixed Process Model
CDRI	Cambodian Development Research Institute
CRE	Correlated Random-Effects
DEA	Data Envelopment Analysis
DFG	German Research Foundation
DID	Difference In Difference
DDD	Triple Differences
FAO	Food And Agriculture Organization
GDP	Gross Domestic Product
GSO	Vietnam General Statistic Office
LM	Langrange-Multiplier Test
LR	Likelihood Ratio
IV	Instrumental Variables
IRRI	International Rice Research Institute
KBM	Kernel Based Matching
NIS	Cambodia National Institute of Statistics
OLS	Ordinary Least Squares
PPP	Purchasing Power Parity
PSM	Propensity Score Matching
PSM-DID	Propensity Score Matching with Difference In Difference
SFM	Stochastic Frontier Model
SUP	Seemingly Unrelated Probit Model
SUR	Seemingly Unrelated Regression
TRE	True Random Effects
TVSEP	Thailand Vietnam Socioeconomic Panel
UN	United Nations
USAID	United States Agency for International Development
VIF	Variance Inflation Factor
WB	World Bank
WWF	World Wildlife Fund

Chapter 1. Introduction

1. Problem Statement and Research Motivation

Rural households in developing countries frequently suffer from different types of shocks such as natural disasters, market instability, or illness. As social protection is still underdeveloped in these countries, severe losses of income, assets or labor capacity due to shocks might have severe consequences on household welfare and their livelihoods, potentially pushing them into food insecurity and poverty (Dercon and Hoddinott, 2003; Demeke et al., 2011). Furthermore, households may be forced to use harmful shock-coping strategies such as selling productive assets or sending their children to work (Dabla-Norris and Gündüz, 2014; Khan et al., 2015). This might enable households to smooth their current consumption, but causes detrimental effects on their livelihoods, consequently preventing them from recovering and severely undermining their welfare in the long run. Therefore, it is essential to have a detailed understanding of households' vulnerability and resilience to shocks as it could provide useful information for policymakers and practitioners to design effective programs for protecting the vulnerable population.

Credit is commonly used by households as a major coping strategy in response to shocks (Isoto et al., 2017, Heltberg et al., 2015). However, empirical results regarding the impact of credit on household welfare and on inequality remain ambiguous. On the one hand, access to credit could provide households with liquid capital to purchase farm inputs and to adopt modern technologies, consequently improving their productivity, increasing household living standards, and reducing poverty (see Abosedra et al., 2016; Clarke et al., 2006; Guirkinger and Boucher, 2008; Khandker, 2005; Liverpool and Winter-Nelson, 2010). During the time of hardships, it also helps households to meet urgent needs for production and consumption, preventing them from adopting harmful coping strategies such as selling productive assets or using child labor. It also eliminates the resistance to expand the production activities of risk-averse farmers and promotes them to pursue productive livelihood strategies (Brümmer and Loy, 2008; Jimi et al., 2019). However, ineffective use of credit may push households into severe debt burden (Seng, 2018; Tsai et al., 2016). Furthermore, in case benefits from the credit market are not proportionately distributed, inequality and social instability are possible unintended consequences (Claessens and Perotti, 2007; Jauch and Watzka, 2016).

Rural households are mainly relying on agricultural production and natural resource extraction as their major livelihood strategies. It is estimated that above 30% of the population in low- and middle-income countries work in the agricultural sector (World Bank, 2020). Their farming methods highly depend on weather conditions and rely on simple equipment. Therefore, their productivity is relatively low, and their farming might not be able to provide adequate food and sufficient income to them (Nguyen et al., 2018a). Consequently, other activities such as natural resource extraction are also performed (Walelign, 2017). Natural resource extraction provides a wide range of products such as food, medicine, fuel, and construction materials for fulfilling households' subsistence needs and generating cash income (Angelsen et al., 2014). However, natural resource overexploitation is happening at an alarming rate. Natural forests had been declining by approximately 6.5 million hectares (ha) per year during the period from 2010 to 2015 and the population of vertebrates had been decreasing by about 60% between 1970 and 2014 (FAO, 2016; WWF, 2018). Many of these degraded ecosystems might not be able to fully recover, causing long-lasting consequences for the future provision of natural resources and ecosystem services (Lampert, 2019). Therefore, improved insights into the impact of shocks and other factors on farm production and natural resource extraction is essential to provide useful information for policymakers and practitioners to design effective programs for enhancing agricultural productivity and for environmental conservation.

The given research has been conducted in four low- and middle-income countries in the Southeast Asia region, namely Cambodia, Laos, Thailand and Vietnam. These countries are commonly characterized by a large share of the population living in rural areas and highly depending on agricultural production. In recent decades, they have achieved high rates of economic growth and significant decreases in the poverty ratio. In particular, Cambodia, Laos and Vietnam are among the 20 fastest growing economies in the world during the period from 2010 to 2019 with annual GDP growth on average above 6%. Thailand is also ranked in the top 100 during this period with GDP growth above 3% (World Bank, 2020). However, their achievement is being threatened by several challenges such as growing inequality, decreasing growth in agricultural productivity, and natural resource degradation (Do, 2019; World Bank, 2016). Furthermore, as social protection in these countries is still underdeveloped, households are highly vulnerable to different types of shocks such as illness, market instability and extreme weather which severely undermine their well-being and their livelihoods (see Grabrucker and Grimm, 2020; Klasen and Waibel, 2013; Lohman and Tobias, 2015). Moreover, these Southeast Asian countries are among the most vulnerable to climate change with Vietnam, Thailand, Cambodia ranked among the top 20 most vulnerable countries to climate risks, whereas Laos is among the 90 most vulnerable countries (Eckstein et al., 2019).

2. Research Objectives and Summary of Main Results

This dissertation is structured into five chapters. The first chapter introduces the general introduction including problem statement, research motivation, research objectives and the overall structure highlighting the contributions of the dissertation to research. Chapter 2 to chapter 5 present research papers. The general aim of this dissertation is to (i) assess households' vulnerability and resilience to shocks by examining the impact of shocks on different household well-being indicators and shock-coping strategies, (ii) investigate the role of credit in mitigating negative impacts of shocks, and its effects on household well-being and inequality, and (iii) investigate the impact of shocks, credit and other livelihood factors on agricultural production and natural resource extraction. The more detailed research objectives are outlined in the following - along with the main results - for the individual chapters.

Chapter 2 on “Multiple shocks and household coping strategies in rural Cambodia” focuses on (i) investigating the impact of shocks on household consumption and education expenditure, and (ii) examining households’ choice of shock-coping strategies in response to shocks. The paper makes some important contributions to the development economics literature and provides useful information for policymakers in Cambodia. First, to the best of our knowledge, this is the first study in Cambodia to quantify the effect of shocks on household consumption and to identify the strategies households adopt in response to shocks. Second, it is one of the very few studies to analyze the effects of shocks on household education expenditure. Third, while most previous studies separately investigated the impact of a single type of shock on household consumption without considering households’ choice of shock-coping strategies, this study quantifies the effects of different types of shocks on different types of household consumption and coping strategies. It can be shown that some shocks are less insurable than others, and it thus provides useful information for policymakers and development practitioners. It suggests to prioritize and design appropriate social programs for less insurable shocks. Methodologically, the Ordinary Least Squares (OLS) method is used to investigate the impact of shocks on total household consumption per capita and household food consumption per capita. The Heckman two-step model is used to measure the impact of shocks on education expenditure per capita. Lastly, the seemingly unrelated probit model (SUP) is applied to examine the factors affecting the choice of shock-coping strategies. Results show that households are less protected against covariate shocks, particularly floods, droughts and livestock diseases. Floods negatively affect total household consumption and food consumption. Similarly, livestock diseases cause a decline in household education expenditure.

They force households to use the coping-strategies of selling durable assets and extracting natural resources. Although droughts do not significantly affect household consumption, these shocks push households into using child labor, selling durable assets, or extracting natural resources. In contrast, health shocks do not appear to have significant and negative effects on household consumption. In response to this type of shock, households tend to use risk-sharing strategies such as borrowing and receiving assistance from friends and relatives. In addition to shocks, some household and village characteristics also have significant effects on household shock-coping strategies. The likelihood of using child labor is positively associated with household size, share of children and age of household head. Households with larger household sizes and living far from markets are more likely to sell assets to cope with shocks. Households are less likely to extract natural resources if they have a lower share of male adults and a higher share of old members and non-farm occupations. Living in a village with better socioeconomic conditions also discourages households to participate in natural resource extraction. Ethnic minority households with older household heads and higher shares of old members are less likely to have access to credit. Meanwhile, households with a larger share of old members tend to receive more assistance from friends and relatives in response to shocks.

Chapter 3 on "Credit and Ethnic Consumption Inequality in the Central Highland of Vietnam" aims (1) to investigate the differences between ethnic groups in accessing credit, particularly in terms of credit sources, amount, interest rate, and the collateral ratio, (2) to examine the differences between ethnic groups in the impact of formal and informal credit on household consumption, and (3) to analyze the impacts of formal and informal credit on the ethnic consumption inequality. To our understanding, this is pioneer work to analyze the impact of credit on inequality between ethnic groups in Vietnam. Moreover, is is differentiated between the effects of formal and informal credit on the consumption of not only the majority ethnic group but also of two different ethnic minority groups. In addition, the differences in interest rates and collateral ratios between ethnic groups are investigated. Econometric methods, namely triple differences with fixed effects, could deal with endogeneity problems related to access to credit and statistically compare the effect of credit on household consumption between ethnic groups. Methodologically, the conditional-mixed process model (CMP) is applied to estimate simultaneously household borrowing decisions. Then, the triple difference with the fixed effects approach (DDD) is applied to examine the heterogeneous impacts of credit by ethnic groups. Lastly, the propensity score matching (PSM) method and Theil's L decomposition method are applied to analyze the impact of formal and informal credit on ethnic consumption inequality. Results show that the indigenous minority households appear to have more disadvantages in accessing formal credit sources than the Kinh majority. They are less likely to access formal sources and rely more on informal ones to satisfy their financial demand. To access formal credit, they face a higher collateral ratio and the amount of formal credit they could access is lower than for the Kinh majority. Regarding the impact of credit on consumption, findings reveal that access to credit significantly and positively affects household consumption of ethnic majority households and this impact is significantly higher than that of indigenous minority households. Furthermore, findings show that a formal credit market may worsen the inequality between ethnic groups in the region due to the disadvantages of indigenous minority households in accessing formal credit as well as their lower efficiency in using loans. Meanwhile, the impact of informal credit on household consumption in each ethnic group as well as on the consumption inequality between ethnic groups is shown to be statistically insignificant. Informal credit is likely to be used as a main coping strategy against income shocks.

Chapter 4 on "Shocks, Credit and Production Efficiency of Rice Farmers in Vietnam" investigates the impact of shocks and credit on the production efficiency of rice farmers in Vietnam, and then examines whether credit plays a role in mitigating the impact of shocks on the efficiency. The main contribution of this research is that the effect of shocks on the relationship between credit and farm efficiency is taken into account. Second, although the effects of shocks and credit on crop yields were investigated, these impacts on agricultural efficiency have been paid little attention to. High yields do not necessarily lead to high efficiency because farmers could increase their yields by using more inputs, but not efficiently utilize inputs. Third, previous studies mainly focused only on climatic shocks, while this study examines the impact of different types of shocks, including weather shocks, health shocks, and market shocks. Last, reporting shocks and access to credit are potentially endogenous, which might cause inconsistent and biased estimates. However, this endogeneity problem has not been taken into account in the literature. In this study, the correlated-random effects approach (CRE) is applied to deal with this endogeneity problem. Methodologically, the stochastic frontier model with correlated random-effects (CRE) adjustment is used to measure the impact of credit and shocks on farm production efficiency. Findings show that weather shocks and land fragmentation are major sources of inefficiency. Meanwhile, livestock, farm mechanization and education are factors promoting rice production efficiency. Results also show that access to credit plays a significant role in mitigating the negative impact of weather shocks. The paper calls for more assistance and support to farmers in mitigating the severe effects of weather shocks, in particular via the promotion of rural credit markets. In addition, it encourages farm mechanization, land defragmentation, and livestock keeping. The improvement of rural education should be also given high priority to improve rice production efficiency.

Chapter 5 on “Shocks, Agricultural Productivity and Natural Resource Extraction in Southeast Asia” aims to (i) examine the impact of shocks on agricultural productivity, and (ii) to investigate the impact of agricultural productivity and shocks on natural resource extraction. This study makes some important contributions to the economics literature and provides useful information for policymakers. First, our understanding regarding the impact of agricultural productivity on natural resource extraction is enhanced, which has received little attention in the previous literature, and results remain ambiguous. Second, endogeneity problems in estimating the impact of agricultural productivity on natural resource extraction are dealt with, which has been largely ignored in the literature. Third, while previous studies on natural resource extraction are often site-specific, making the generalization of research findings difficult, this study is conducted in four different countries. Fourth, the study quantifies the effects of different types of shocks, whereas previous studies tend to focus on a single type of shock. Methodologically, OLS regression is applied to estimate the impact of shocks on agricultural productivity. Then, heteroscedasticity-based instrument models are used to investigate the impact of agricultural productivity on natural resource extraction. Findings show that weather shocks and market shocks are among the factors that significantly push households to extract more natural resources and enhancing agricultural productivity could discourage natural resource extraction. In addition, it shows that household education, the availability of enterprises and electricity access in the village are negatively associated with natural resource extraction. It is recommended that measures for enhancing agricultural productivity should be prioritized and more assistance and support to farmers for mitigating the severe effects of weather shocks and market shocks should be provided. Furthermore, promoting rural education, accelerating rural electrification, and supporting the development of local enterprises should also be implemented.

3. Publication Status of Papers and Author’s Contribution

Table 1 presents the overview and information about the publication status of all the papers included in the dissertation. Chapters 2 and 3 are published in the journals *Ecological Economics, and Social Indicators Research,* respectively, whereas chapters 4 and 5 are in the peer-review processes.

Table 1. List of papers included in the dissertation

Chapter	Authors	Title	Published in / Submitted to / Presented at
2	**Nguyen, T.T.,** Nguyen, T.T., and Grote, U.	Multiple shocks and households' choice of coping strategies in rural Cambodia	Published in *Ecological Economics* (2019), 167(106442). doi: 10.1016/j.ecolecon.2019.106442 Presented at the Conference of The Society of Economics of the Household (SEHO), Lisbon, Portugal in 2019
3	**Nguyen, T.T.**, Nguyen, T.T., and Grote, U.	Credit and Ethnic Consumption Inequality in the Central Highlands of Vietnam	Published in *Social Indicators Research* (2019), 148, 143-172, doi: 10.1007/s11205-019-02202-z Presented at the Conference of Poverty Reduction, Equity and Growth Network (PEGNET), Bonn, Germany in 2019
4	**Nguyen, T.T.**, Nguyen, T.T., and Grote, U.	Credit, Shocks and Production Efficiency of Rice Farmers in Vietnam	Previous version is published in TVSEP working paper series: Nguyen, T.T., Nguyen, T.T., and Grote, U. (2020). Weather shocks, credit and production efficiency of rice farmers in Vietnam. TVSEP Working Paper WP-017. Thailand Vietnam Socio Economic Panel, Leibniz Universität Hannover
5	**Nguyen, T.T.,** Nguyen, D.L., Do, M.H., Nguyen, T.T., and Grote, U.	Shocks, Agricultural Productivity and Natural Resource Extraction	Presented at 31st International Conference of Agricultural Economics in 2021

Note on author's contribution: With respect to Chapter 2, the author was mainly responsible for conceptualization, writing and data analysis, whereas Trung Thanh Nguyen and Ulrike Grote gave the idea of analyzing the impact of shocks on household education expenditure and supported the paper in conceptualization, peer-review, and proofreading. Chapters 3 and 4 have been mainly developed, conceptualized, researched, and written by the author, whereas the co-authors Ulrike Grote and Trung

Thanh Nguyen gave advice and correction on writing, conceptualization, and support during the peer-review and proofreading process. Chapter 5 is the result of co-authorship with Duy Linh Nguyen, Manh Hung Do, Trung Thanh Nguyen and Ulrike Grote. The author was all responsible for conceptualization, data analysis, and writing. In addition, Duy Linh Nguyen and Manh Hung Do contributed to writing a part of the literature review and study design, whereas Trung Thanh Nguyen and Ulrike Grote supported the paper during the proofreading and peer-review process.

The author was also involved as a co-author in writing papers which are not presented in the thesis:

Nguyen, T. T., **Nguyen, T.T.**, Hoang, V. N., Wilson, C., & Managi, S. (2019). Energy transition, poverty, and inequality in Vietnam. *Energy Policy*, 132, 536-548.

Nguyen, T. T., **Nguyen, T. T.**, Le, V. H., Managi, S., & Grote, U. (2020). Reported weather shocks and rural household welfare: Evidence from panel data in Northeast Thailand and Central Vietnam. *Weather and Climate Extremes*, 100286.

Nguyen, T. T., Tran, V. T., **Nguyen, T. T.,** & Grote, U. (2021). Farming efficiency, cropland rental market and income effect: evidence from panel data for rural Central Vietnam. *European Review of Agricultural Economics*, 48(1), 207-248.

Sharma, R., **Nguyen, T.T.**, Grote, U., & Nguyen, T. T. (2016). Changing livelihoods in rural Cambodia: Evidence from panel household data in Stung Treng. ZEF Working Paper 149, Center for Development Research (ZEF), Bonn.

The author also took part in the field survey of TVSEP 2016 for collecting and managing the household and village data in Vietnam, and was involved in checking interviewed household questionnaires for TVSEP in 2017.

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Chapter 2. Multiple Shocks and Households' Choice of Coping Strategies in Rural Cambodia

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Chapter 3. Credit and Ethnic Consumption Inequality in the Central Highlands of Vietnam

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Chapter 4. Credit, Shocks and Production Efficiency of Rice Farmers in Vietnam

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Abstract

Enhancing rice production efficiency in developing countries is important to improve the livelihoods of farmers and to ensure global food security for a growing population. Despite significant progress in recent decades, rice production is facing multiple challenges from climate change to the increasing competition for land, labor and capital from urbanization and industrialization. Given the fact that Vietnamese farmers often suffer from shocks and financial capital constraints, our paper aims to (i) investigate the impact of credit and shocks on rice production efficiency, and to (ii) examine the role of credit in mitigating the impact of shocks. Our findings show that weather shocks and land fragmentation are major sources of the inefficiency. Meanwhile, livestock, farm mechanization, and education are factors promoting rice production efficiency. Our results also show that access to credit plays a significant role in mitigating the negative impact of weather shocks. Our paper calls for more assistance and support to farmers in mitigating the severe effects of weather shocks, in particular via the promotion of rural credit markets. In addition, the encouragement of farm mechanization, land defragmentation, livestock farming, and the improvement of rural education should be given high priority to improve rice production efficiency.

1. Introduction

Rice is one of the most important food crops in the world. It is estimated that more than half of the world population depend on rice for more than 20 per cent of their daily calorie intake and that more than one billion people undertake rice production as their main livelihood activities (FAO, 2014a). Therefore, improving rice production efficiency is crucial to enhance the welfare of rural farmers and to ensure global food security (Amare et al., 2018). Since the Green revolution, rice productivity has dramatically increased, but this growth is still insufficient to keep pace with the growth of the world population (FAO, 2014b). It is expected that our world still needs an additional 100 million tons of rice by 2035, equivalent to an annual yield increase of about two per cent to feed the growing population (Seck et al., 2012). However, the growth in rice productivity has slowed considerably in recent decades, falling from two per cent per year in the 1970s to less than one per cent in the 2000s (IRRI et al, 2011). Meanwhile, the possibility for expanding rice-cultivated area remains very limited as arable lands are mostly exploited (Duwayri et al, 2000). Moreover, rice production is suffering from several challenges ranging from global climate change, water scarcity, and land degradation to the increasing competition for land and labor from the urbanization and industrialization (FAO, 2014b; IRRI et al, 2011).

Credit is commonly considered an important source of finance for rural households in developing countries (Guirkinger and Boucher, 2008; Ali et al., 2014). It provides households with liquid capital to purchase farm inputs and to adopt modern technologies (Isoto et al., 2017). However, empirical evidence on the relationship between credit and farm efficiency remains ambiguous. On the one hand, if credit is used effectively, it could enhance farm efficiency by relieving households from financial constraints, motivating investments in farm infrastructure, and accelerating the adoption of modernized inputs and technologies (Brümmer and Loy, 2000; Jimi et al., 2019). Credit can also enhance households' resilience to shocks, therefore eliminating the resistance to expand the production activities of risk-adverse farmers as well as ensuring the continuity and the recovery of the production processes (Jimi et al., 2019). On the other hand, it is argued that due to market imperfections, lack of knowledge and information, and other constraints, households may not be able to optimize their investment; consequently, access to credit will not translate into higher farm efficiency (Taylor et al., 1986; Jimi et al., 2019). In addition, the ineffective use of credit may cause heavy debt burden, default and deteriorate their production processes (Nguyen et al., 2020a; World Bank, 2009; Seng, 2018).

Rural households in developing countries also frequently suffer from different types of shocks. As agricultural production in these countries is highly labor-intensive and depends largely on weather conditions, the occurrence of shocks such as extreme weather events (Mishra et al., 2018) or health shocks (Isoto et al., 2017) might have severe consequences on agricultural production. For example, rainfall shocks lead to crop failure; market and health shocks could prevent farmers from using the optimal level of inputs or discourage them from using productivity-enhancing external inputs. In addition, due to the lack of social insurance mechanisms and imperfect credit markets, households may adopt harmful shock-coping strategies such as selling land or depleting productive assets (Dabla-Norris and Gündüz, 2014; Khan et al., 2015). This might enable households to smooth their consumption in the short run, but cause detrimental effects on their farm activities, consequently jeopardizing their livelihoods and their welfare in the long run.

Based on a panel dataset from Vietnam, our paper first aims to investigate the impact of shocks and credit on the efficiency of rice production, and then examines whether credit plays a role in mitigating the impact of shocks on the efficiency. Vietnam is a suitable location for our research as (i) it is a developing country with the economy highly depending on agricultural production, (ii) rice is the most important food crop in Vietnam, contributing more than 40 per cent in the net production value of crops and occupying more than 40 per cent of the agricultural land area (World Bank, 2016; USAID, 2017), and (iii) the growth in total factor productivity of rice production has considerably declined in recent years (World Bank, 2016). Our paper contributes to the current literature in some important aspects. First, although the effects of shocks and credit on crop yields were investigated (see Ali et al., 2014; Guirkinger and Boucher, 2008; Isoto et al., 2017), the impacts of credit on agricultural efficiency have gained little attention. High yields do not necessarily lead to high efficiency because farmers could increase their yields by using more inputs, but not utilizing inputs efficiently (Yang et al., 2016). Second, previous studies did not account for the effect of shocks on the relationship between credit and farm efficiency. This study extends the existing literature by investigating how farm efficiency is affected by shocks and whether efficiency losses can be mitigated by credit. Third, previous studies mainly focused on climatic shocks; our paper examines the impact of different types of shocks, including weather shocks, health shocks, and market shocks. Last, reporting shocks (Nguyen and Nguyen, 2020) and access to credit (Nguyen et al., 2020a) are potentially endogenous, which might cause inconsistent and biased estimates. However, this endogeneity problem has not been tackled in the literature. In this study, we apply the correlated-random effects approach (CRE) to deal with this endogeneity problem.

The rest of the paper is structured as follows. Section 2 reviews the literature. Section 3 describes the data source and methodologies. Section 4 shows the results and discusses the findings. Section 5 summarizes and concludes.

2. Theoretical Background and Literature Review

2.1. Measuring Farm Production Efficiency

Efficiency is a basic notion in economics. It interrelates inputs and outputs of production activities. Farm efficiency can be determined by referring either to the inputs or outputs utilization. The output-oriented efficiency measurement evaluates the capability of farmers to maximize their outputs with a given amount of inputs, whereas the input-oriented efficiency measurement evaluates the capacity to minimize the inputs used for a specific amount of outputs. For the purpose of our study, the output-oriented model is selected. Based on the output-oriented model, a farm is fully efficient if it could not increase the amount of outputs without increasing their inputs. Farm efficiency is measured as the ratio of the observed amount of outputs to the amount of outputs of a fully efficient farm (Farrell, 1957, Khanal et al., 2018). As the production function of the fully efficient farm is unknown, it has to be estimated (Battese and Coelli, 1995). In the literature, farm efficiency could be estimated either with the non-parametric approach of Data Envelopment Analysis (DEA) or with the parametric approach of Stochastic Frontier Model (SFM). However, the DEA approach does not take into account measurement errors and other sources of statistical noise; therefore, SFM is favored in analyzing the farm efficiency (Hardaker et al., 2004; Coelli et al., 2005; Nguyen et al., 2018). The SFM is specified as follows:

$$Q_i = \exp(\beta x_i + v_i - u_i(\delta z_i + \epsilon_i)) \quad (1)$$

where Q_i is the outputs of farm i. x_i represents the vector of inputs. v_i is the symmetric random error accounting for noise effects. The farm technical inefficiency is represented by the non-negative variable u_i, which could be expressed as a function of exogenous factors z_i that affect the technical efficiency. Farm technical efficiency is the ratio of the observed outputs to the frontier outputs and is specified as:

$$\Gamma_i = E[\exp(-u_{it}) \,|(v_{it} - u_{it})] = \frac{\exp(\beta x_i + v_i - u_i)}{\exp(\beta x_i + v_i)} \quad (2)$$

The measure of farm technical efficiency ranges from zero to one. The value of zero indicates that the farm is fully inefficient, whereas the value of one implies that the farm is fully efficient.

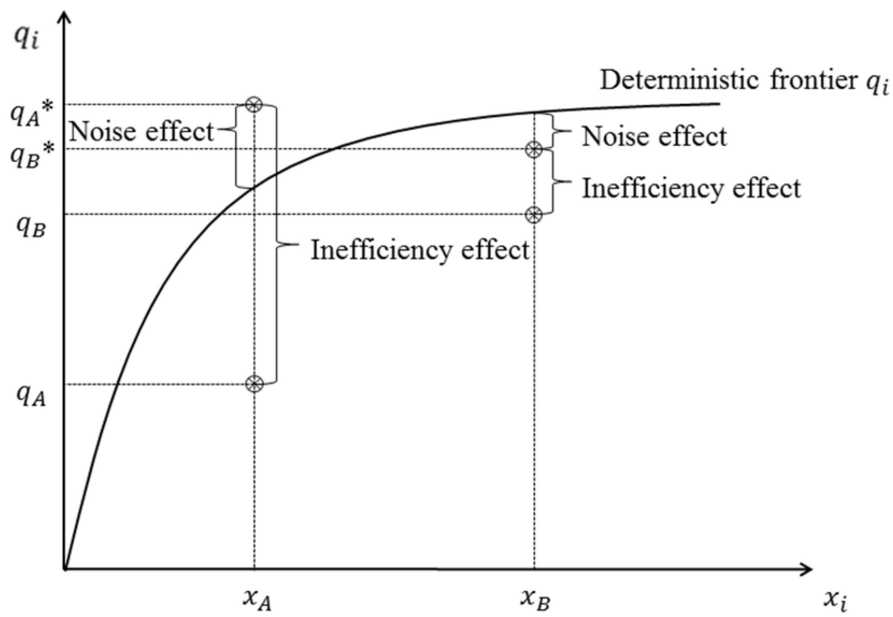

Figure 1. The Stochastic Production Frontier (Source: Coelli et al., 2005; Ebers et al., 2017)

Figure 1 illustrates the basic features of the SFM with an example of two farms i = {A, B}, using one input x_i (horizontal axis) to produce one output q_i (vertical axis). Farm A uses x_A inputs to produce the q_A observed outputs. Farm B uses x_B inputs to produce q_B observed outputs. In case that farm A and farm B are fully efficient (u_A=0, u_B=0), their frontier outputs are q_{A^*} and q_{B^*}, respectively. Because of the noise effect, the frontier outputs vary around the deterministic frontier. If the noise effect is negative (farm B: v_B <0), the frontier outputs lie below the deterministic frontier. In contrast, the frontier outputs are above the deterministic frontier if the noise effect is positive (farm A: v_A >0). The observed outputs must lie below the deterministic frontier. It can only lie above the deterministic frontier if the noise effect is positive and its effect is larger than the inefficiency effect ($v - u$ >0). The features of this model could also generalize to the multi-output, multi-input cases (Coelli et al., 2005; Nguyen et al., 2018).

2.2. Credit, shocks, and farm production efficiency

Credit is commonly considered an important instrument to relieve households of financial capital constraints, subsequently promoting investment in income-generating activities and enhancing household welfare (Nguyen et al., 2020a). Conceptually, relaxing credit constraints could positively affect farm productivity and efficiency as it enables farmers to invest in modern technologies, to adopt more productive crop varieties, and to utilize complementary production inputs in a timelier manner (Jimi et al., 2019). However, empirical studies show that the impact of credit on farm efficiency remains ambiguous. On the one hand, studies from Ghana (Abdallah, 2016), China (Zhao and Barry, 2014), Bangladesh (Afrin et al., 2017), and Cambodia (Mishra et al., 2018) show that access to credit significantly improves farm efficiency. On the other hand, other studies show that access to credit does not significantly improve farm efficiency or even negatively affects the efficiency. Taylor et al. (1986) show that access to credit does not have any effects on the efficiency of traditional farmers in Brazil. This is consistent with Abdulai et al. (2018), who show that the impact of credit on farm efficiency in Ghana is insignificant. The studies of Brümmer and Loy (2000) in Germany and of Ebers et al. (2017) in Cambodia show that access to credit even leads to a decrease in farm efficiency. It is argued that although credit availability could enable traditional farmers to invest in modernized technologies and to adopt yield-enhancing inputs, it is possible that these households are not able to use them in an appropriate way to achieve the full extent of output gains (Rezitis et al., 2003). The lack of knowledge and management skills may prevent households from optimizing their investment (Taylor et al., 1986). In addition, if loans are not efficiently used, the severe burden of debt service might inhibit and deteriorate their production processes (see World Bank, 2009; Ebers et al., 2017; Seng, 2018).

A number of studies have investigated the impact of shocks on farm productivity, but to the best of our knowledge, only few studies (Mishra et al., 2015; Mishra et al., 2018) have investigated the impact of weather shocks on agricultural efficiency, and none have analyzed the impact of health shocks or market shocks on farm efficiency. Mishra et al. (2015) examine the impact of extreme weather events in Bangladesh showing that floods and droughts are major contributors to the inefficiency of rice farmers. Mishra et al. (2018) analyze the impact of access to credit and extreme weather events on the production efficiency of rice farmers in Cambodia. Their findings reveal that drought is among the major sources of inefficiency of rice production, whereas access to credit could help farmers to improve their efficiency. However, they do not show whether access to credit could mitigate the negative impact of shocks or not. Isoto et al. (2017) examine the role of credit in mitigating the impact of shocks on agricultural production. However, they focus on agricultural productivity instead of agricultural efficiency, and find that health shocks negatively and significantly affect crop yields of farmers in Uganda. In addition, their results also reveal that access to credit plays an important role in reducing productivity losses due to health shocks.

With regard to Vietnam, several studies have investigated determinants of rice production efficiency (Khai et al., 2011; Vu et al., 2012; Nguyen et al., 2019). However, only few studies take into account the impact of credit on agricultural efficiency and their result are inconsistent. Kompas et al. (2012) show that access to credit could significantly eliminate the inefficiency of rice production in Vietnam. Meanwhile, Linh et al. (2015) show that the impact of credit on rice production efficiency in Vietnam is insignificant. Duy et al. (2015) disaggregate credit into formal and informal sources and show that both these credit sources significantly enhance rice production efficiency. Methodologically, a common limitation in these studies is that they do not take into account the potential endogeneity problem in estimating the impact of credit on farm efficiency. As access to credit is likely correlated with some household characteristics (Barslund and Tarp, 2008; Nguyen et al., 2020a), failure to control for unobserved characteristics may lead to biased and inconsistent estimates.

3. Study Sites and Data Analysis

3.1. Study sites and data sources

Vietnam is a developing country with the economy highly depending on agricultural production. The agricultural sector accounts for around 40 per cent of the employment and 20 per cent of the total gross domestic product (GDP) (World Bank, 2016). Rice is the most important food crop in Vietnam, contributing more than 40 per cent in the net production value of crops and occupying more than 40 per cent of the agricultural land area (see World Bank, 2016; USAID, 2017). In recent decades, Vietnam has also achieved explosive growth in agricultural production, transitioning from a country which once experienced hunger to one of the top rice exporting countries in the world. However, the growth in rice total factor productivity has considerably declined in recent years (World Bank, 2016). In addition, rice production in Vietnam is facing severe threats from climate change as well as growing land degradation and water pollution. Located in the Southeast Asia region, Vietnam is among the top ten most vulnerable countries to climate risks. USAID (2017) reports that natural disasters caused nearly ten thousand fatalities and were responsible for losses equal to 1.5 per cent of the annual GDP between 2001 and 2010. It is forecasted that the impact of climate change on Vietnam's agriculture could result in a reduction of around 2 per cent of total GDP in 2050 (USAID, 2017; Trinh, 2018).

This study uses a three-year balanced panel dataset, collected in 2010, 2013 and 2016 under a rural research program funded by the German Research Foundation (DFG). This program includes two consecutive projects. The first one is ‘Impact of shocks on the vulnerability to poverty: Consequences for the development of emerging Southeast Asian Economies (DFG FOR 756/1)’ and the second one is 'Poverty dynamics and sustainable development: A long-term panel project in Thailand and Vietnam, 2015 – 2024 (DFG FOR 756/2 (TVSEP))'[1].The surveyed area, samples and the data collection procedures between these two projects are similar. The survey in Vietnam is conducted in three provinces, namely Ha Tinh, Thua Thien Hue and Dak Lak (Figure 2). These provinces are characterized by (i) a high dependence on agriculture, (ii) a low average income per capita, and (iii) a relatively high expose to extreme weather events (Hardeweg et al., 2012; Do et al., 2019).

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

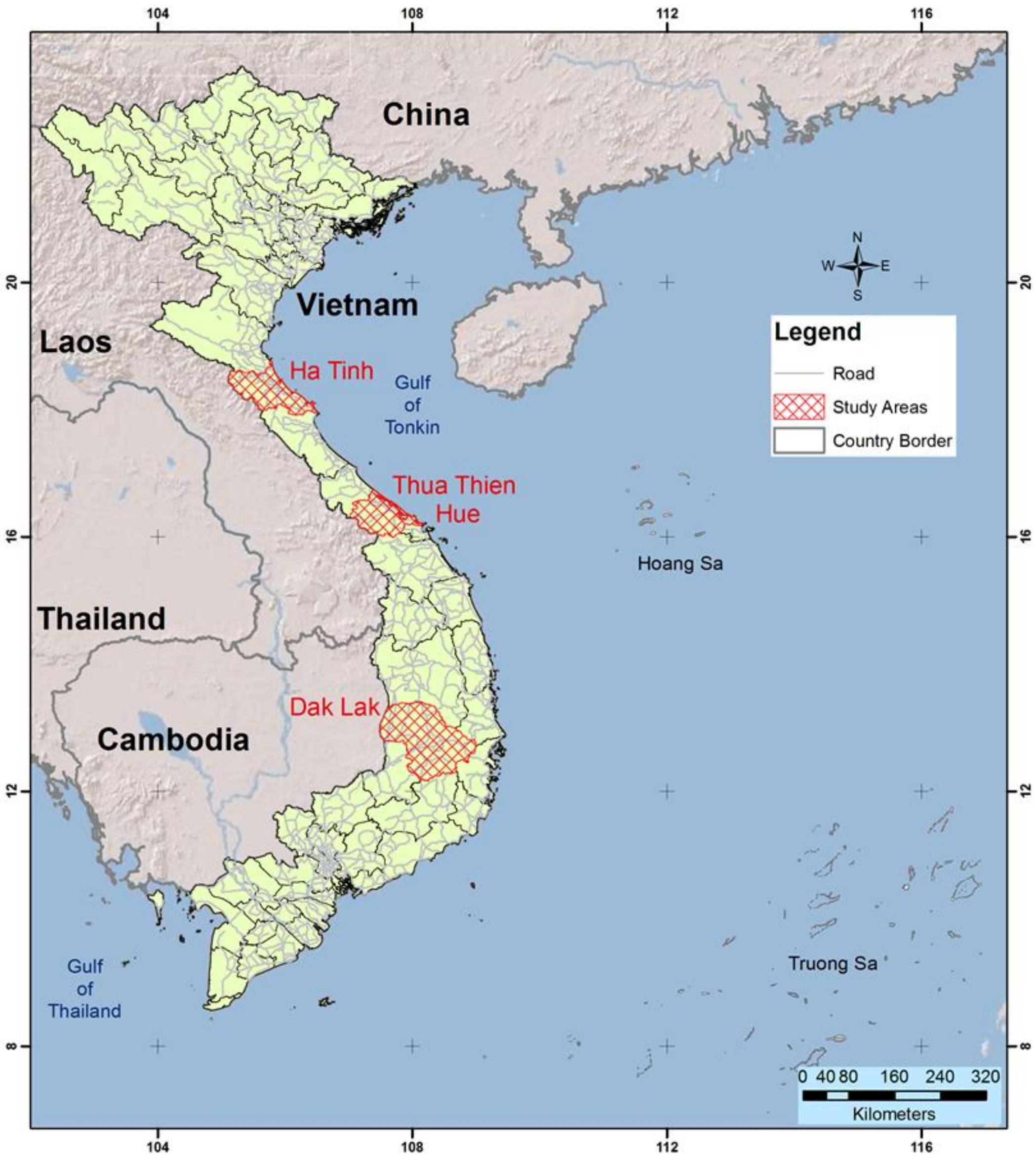

Figure 2. Map of surveyed provinces in Vietnam (source: Nguyen et al., 2020b)

The data collection follows a three-stage cluster sampling procedure (Hardeweg et al., 2012; Nguyen et al., 2020c). The first stage is the selection of surveyed commune within provinces. Because the size of the commune population is not available at the time of sampling, the population share of respective districts is used to select sampled communes. At the second stage, 220 villages (2 villages in each sampled commune) were sampled with probability proportional to the size of the village's population. At the last stage, 10 households in each sampled village were randomly chosen from a list of households with equal probability selection. For the purpose of our study, which focuses on rice production efficiency, we restrict our sample to households which have rice cultivated-area during the surveyed period and are observed in all three waves of 2010, 2013 and 2016. In this regard, our sample includes 3000 observations of 1000 farmers.

A household questionnaire is used to collect detailed information on the individual households (age, household size, ethnicity, education, and health), household livelihood activities (crop farming, livestock rearing, hunting, non-farm employment), credit, investment, asset, and expenditure. In particular, a shock section includes information on types of shock events, time of occurrence, severity, and losses. Regarding a section on borrowing, detailed information on the value, source, time, and duration of loans is collected. A farm section captures information on crop varieties, planted area, total outputs, sales prices, and expenditure for land preparation, for seeds and seedlings, fertilizers, pesticides, weeding, harvesting, and irrigation.

3.2. Data Analysis

There are two main approaches in the literature of production efficiency analysis using stochastic frontier model, namely the two-step stochastic frontier model and the one-step stochastic frontier model (Nguyen et al., 2012; Yang et al., 2016). In the former, the production efficiency score for each farmer is estimated after the stochastic frontier production function is estimated. Then, the estimated efficiency score is regressed on potential explanatory variables. However, this approach is criticized as it does not take into account the correlation between household characteristics and farm input characteristics. In addition, even if this correlation does not exist, biased estimates of the inefficiency score may also result from the misspecification of the first step, which ignores the impact of household characteristics on inefficiency. This problem is similar to the omitted variable problem in the linear regression (Yang et al., 2016). Therefore, our paper adopts the latter approach, namely the one-step stochastic frontier model. This approach overcomes the limitation of the former by simultaneously estimating the stochastic frontier production function and the production inefficiency function.

A problem in estimating the impacts of credit and shocks on farm efficiency is the potential endogeneity problem (Arouri et al., 2015; Kislat, 2015). These variables are likely correlated to unobservable household characteristics and failure to control for these unobservable variables potentially lead to biased and inconsistent estimates. Therefore, we follow Yang et al. (2016) to apply the correlated random-effects (CRE) approach, including the time average of potentially endogenous variables to control for unobserved households characteristics. In addition, as we have panel data, our estimations are conducted by the True Random Effects approach[2] (TRE) (Greene, 2005), an extension of the standard random-effect approach of Pitt and Lee (1981) to separate the sources of time-invariant heterogeneity and the inefficiency component. As the likelihood-ratio test shows that the Translog function form is more appropriate than the Cobb-Douglas function form (see Appendix A1), our model is specified as follows:

$$\ln Y_{it} = \alpha_0 + \omega_i + \sum_{1}^{m} \alpha_m lnx_{mit} + \frac{1}{2}\sum_{1}^{m}\sum_{1}^{n} \alpha_{mn} lnx_{mit} lnx_{nit} + V_{it} - U_{it} \tag{3}$$

with

$$U_{it} = \beta_0 + \beta_1 C_{it} + \beta_2 S_{it} + \beta_3 H_{it} + \beta_4 P_{it} + \beta_5 Y_i + \beta_6 \bar{C_i} + \beta_7 \bar{S_i} + \beta_8 \overline{H_i} + \epsilon_{it} \tag{4}$$

where Y_{it} is the total value of rice outputs of household i at time t. x_{it} is the vector of inputs. The input variables are harvested land, land preparation cost, irrigation cost, fertilizer cost,

[2] True Fixed Effects Stochastic Frontier model is not used in our paper as it could cause severely biased results when the length of panel data is short (T<10) or the ratio of number of unit is quite large compared to the length of the panel (Abdulai and Tietje, 2007; Belotti et al., 2013).

pesticide cost, seed and seedling cost, harvesting cost, other input costs, and the number of household labourers working on their own farm. In our model, monetary variables are converted to 2005 PPP US dollar. ω_i denotes farm-specific and time-invariant heterogeneity. V_{it} is the error term to capture noise effects. U_{it} is the production inefficiency term and is regressed on a set of variables including household livelihood assets and livelihood activities, year, province and time average of potentially endogenous variables. C_{it} is a dummy variable indicating whether household i at time t accesses credit or not. In addition, we also estimate our models with dummy variables of access to informal credit and access to formal credit. S is the vector denoting shock characteristics. This includes weather shocks (floods, droughts, storms, and cold periods), health shocks (illness, death) and market shocks (strong decrease of prices for outputs or strong increase of prices for inputs) that households suffered in the last 12 months. To prevent reporting and measurement errors, we drop shock events that are reported to have no impact and cause no losses. H is the vector of household livelihood assets and activities. This includes households' human capital (age of household head, education of household head, household size, share of children), physical capital (number of tractors, the value of livestock, number of motorbikes), social capital (ethnicity, number of phones), financial capital (the value of received remittances), natural capital (owned agricultural land, agricultural land fragmentation), livelihood activities (having migrant members, having non-farm employment). P and Y are province and year dummy variables, respectively. $\bar{C}, \bar{S}, \bar{H}$ are the time average of C, S and H, respectively. These variables are used to control unobserved variables and the sign of these variables do not have meaningful interpretations (Yang et al., 2016; Gautam and Ahmed, 2018). For household head characteristic variables such as ethnicity, we do not include the time average of these variables because these variables are likely exogenous and their values are almost unchanged during surveyed years. All variables of inputs in Equation 3 are normalized by dividing their observed values by their respective sample mean before estimation, then the coefficients on the first order term can be read directly as elasticities at means (see Yang et al., 2016; Holtkamp and Brümmer, 2017). The detailed information of explanatory variables are given in Appendix A2.

To examine the role of credit in mitigating the impact of shocks on farm production efficiency, we add the interaction between credit and shocks into Equation 2. This estimation is then specified as:

$$U_{it} = \theta_0 + \theta_1 C_{it} + \theta_2 S_{it} * C_{it} + \theta_3 S_{it} + \theta_4 H_{it} + \theta_5 P_{it} + \theta_6 Y_i + \theta_7 \bar{C}_i + \theta_8 \bar{S}_i + \theta_9 \bar{H}_i + \mu_{it} \quad (5)$$

The sign of θ_3 indicates the impact of shocks on farmers who have no access to credit. The sum of θ_2 and θ_3 indicates the impact of shocks on farmers who have access to credit. If $\theta_3 > 0$ and $\theta_2 > 0$, then $(\theta_2 + \theta_3) > \theta_3 > 0$. This indicates that shocks have negative impacts on production inefficiency in both groups of households, with or without access to credit. In addition, this effect is more severe in the groups of households with access to credit. If $\theta_3 > 0$, but $\theta_2 < 0$, then $(\theta_3 + \theta_2) < \theta_3$. This indicates that the negative impact of shocks on the production efficiency is more severe in the group of households without access to credit. In other words, it shows that access to credit plays a significant role in mitigating the negative impact of shocks on production efficiency. As robustness checks, we also estimate the efficiency with the Cobb-Douglas production function. Furthermore, the dependent variable in Equation 3, which is the value of total outputs (in PPP$), is replaced by the quantity of outputs (in tons). The results of these robustness checks are highly consistent with our main findings (see Appendices A3 and A4).

4. Results and Discussion

Table 1 compares households' characteristics between two household groups, with and without access to credit. Generally, the former is more likely to report that they suffer from weather shocks, health shocks as well as market shocks. An explanation is that access to credit is commonly found as a major strategy to cope with different types of shocks (Heltberg and Lund, 2009; Yilmaz et al., 2014). For demographic characteristics, households with access to credit appear to have younger household heads, larger household sizes, and higher shares of children. This is consistent with the life-cycle hypothesis that households at the early stage of their lifespan may not accumulate enough physical and financial capital; therefore, they are more likely to borrow to satisfy their consumption and production purposes. Our results also show that households without access to credit appear to have a higher value of received remittances. Ambrosius and Cuecuecha (2013) also reveal that remittances have substitution effects on households' decision to access credits. An explanation is that households could satisfy their financial demand by receiving remittances, therefore, they may not need credit. With respect to cropland and productive assets, households without access to credit appear to have a smaller cropland area, a lower value of livestock, and fewer assets (tractors, motorbike, and phones). This is reasonable as households with a higher endowment level of productive assets such as land and livestock holdings may have a higher demand for credit to satisfy their production purposes (Barslund and Tarp, 2008).

Table 2 reports farm input-output characteristics. Generally, farmers spend the highest expenditure on fertilizer. This amount is above 400 PPP $ per ha, more than twice as high as the second and the third highest expenditures for harvesting and land preparation, respectively. This is consistent with results from the World Bank (2016) reporting that agricultural production in Vietnam is featured by the intensive use of fertilizer. Fertilizer is the highest single cost-item in rice production with application rates per ha being about 30-200 per cent higher than that of other Southeast Asian countries (World Bank, 2016). Comparing households with and without access to credit, the former appears to spend more on inputs such as fertilizers, pesticides, land preparation, and seeds. However, their outputs are only negligibly higher than the latter.

Table 1. Characteristics of households with and without credit access

	Whole sample	Without Credit	With Credit
weather shock	30.633	27.811***b	33.467***b
(%)	(46.105)	(44.822)	(47.203)
health shock	20.533	18.363***b	22.712***b
(%)	(40.401)	(38.731)	(41.911)
market shock	4.467	3.792*b	5.144*b
(%)	(20.661)	(19.108)	(22.096)
remittance	1060.669	1212.809***a	907.92***a
(PPP $)	(2926.976)	(3557.27)	(2103.078)
household size	4.199	4.055***a	4.343***a
(people)	(1.651)	(1.608)	(1.683)
child share	19.665	18.758**b	20.575**b
(%)	(20.948)	(21.075)	(20.786)
age head	51.593	52.747***a	50.435***a
(years)	(11.687)	(12.557)	(10.622)
education head	6.813	6.829	6.796
(years)	(3.881)	(3.978)	(3.783)
ethnic minority	21.867	20.293**b	23.447**b
(%)	(41.341)	(40.231)	(42.381)
phone	1.951	1.904*a	1.998*a
(numbers)	(1.393)	(1.382)	(1.404)
tractor	0.392	0.365***a	0.42***a
(numbers)	(0.563)	(0.539)	(0.585)
motorbike	1.202	1.168**a	1.236**a
(numbers)	(0.909)	(0.925)	(0.891)
livestock value	1840.592	1753.508**a	1928.025**a
(PPP $)	(2418.031)	(2326.266)	(2504.52)
owned farm land	0.619	0.564***a	0.675***a
(ha)	(0.825)	(0.782)	(0.863)
farm land fragmentation	0.114	0.116	0.113
(plots)	(0.443)	(0.406)	(0.477)
having migrants	47.3	46.041	48.564
(%)	(49.935)	(49.86)	(49.996)
having non-farm employment	43.433	43.313	43.554
(%)	(49.575)	(49.567)	(49.599)
No. of observations	3000	1503	1497

**** p<0.01, ** p<0.05, * p<0.1; standard deviation in parentheses; a: Two-sample Wilcoxon rank-sum (Mann-Whitney) test; b: t tests (mean-comparison tests); farm land fragmentation is measured by the number of small farm plots less than 0.02 ha (see Huy & Nguyen, 2019)*

Table 2. Farm input-output characteristics by credit access

	Whole sample	Without Credit	With Credit
fertilizer cost	438.363	410.655***	466.183***
(PPP $ per ha)	(389.938)	(330.011)	(440.369)
pesticide cost	106.213	100.135***	112.315***
(PPP $ per ha)	(112.833)	(111.627)	(113.743)
harvesting cost	198.746	203.549	193.924
(PPP $ per ha)	(845.445)	(1178.036)	(198.792)
land preparation cost	178.108	164.744***	191.525***
(PPP $ per ha)	(188.707)	(161.273)	(211.931)
seed cost	125.559	109.71***	141.473***
(PPP $ per ha)	(165.788)	(149.885)	(178.994)
other cost	64.596	62.484	66.716
(PPP $ per ha)	(164.869)	(204.973)	(110.901)
laborer	2.008	1.921***	2.094***
(laborer per ha)	(0.978)	(0.906)	(1.038)
rice land	0.551	0.539	0.563
(ha)	(0.545)	(0.522)	(0.567)
rice output	1530.921	1496.729	1565.25
(PPP $)	(1916.346)	(1989.36)	(1840.156)
rice yield	2796.971	2794.578	2799.374
(PPP $ per ha)	(1582.76)	(1681.08)	(1478.042)
No. of observations	3000	1503	1497

**** p<0.01, ** p<0.05, * p<0.1; t tests (mean-comparison tests)*

Table 3 reports the estimated coefficients and standard errors of the Stochastic Frontier Model. The results show that the outputs are positively and significantly correlated with almost all input variables, except for the expenditure on land preparation. The elasticity of cropland is the highest (0.68), followed by that of fertilizer (0.13). This result is consistent with Kompas et al. (2012), showing that land and fertilizer are the most important inputs in rice production in Vietnam. World Bank (2016) also reports that the success in Vietnam's agricultural growth in recent decades has come from the intensive use of land and the heavy use of fertilizer. However, it is argued that this practice should not be promoted because it potentially causes severe environmental consequences such as land degradation and pollution (World Bank, 2016). In addition, our findings show that the expenditure on harvesting is the third important input with an elasticity of around 0.07. Harvesting is the process of collecting the mature rice crop, including activities of reaping, stacking, handling, threshing, cleaning, and hauling. A good harvesting method is important to minimize crop losses and quality deterioration (IRRI, 2019). Furthermore, our results indicate that the number of laborers and expenditure on pesticides, seeds, and other inputs (including irrigation and weeding) also significantly contribute to rice outputs.

The overall production efficiency score and the distribution are shown in Figure 3. The average efficiency score is 0.79, highly consistent with Khai et al. (2011) and Kompas et al. (2012). This indicates that Vietnamese farmers, on average, are just producing at around 80 per cent of their maximum capacity and they can improve their outputs by about 20 per cent. In addition, the distribution shows that most of the sampled households (70 per cent) have efficiency scores from 0.7 to 0.9. Around 10 per cent of households have efficiencies higher than 0.9, while less than five per cent of households have efficiency scores of less than 0.5.

Table 3. Translog Stochastic Frontier Production

Translog Stochastic Frontier Production		
	Coefficient	Robust Std. Err.
ln rice land	0.684***	(0.032)
ln fertilizer cost	0.128***	(0.020)
ln pesticide cost	0.034***	(0.013)
ln harvesting cost	0.066***	(0.018)
ln land preparation cost	-0.013	(0.014)
ln seed cost	0.036***	(0.014)
ln other costs	0.054***	(0.010)
ln laborer	0.043**	(0.020)
$(\ln \text{rice land})^2$	0.012***	(0.002)
$(\ln \text{fertilizer cost})^2$	0.004***	(0.002)
$(\ln \text{pesticide cost})^2$	-0.002	(0.001)
$(\ln \text{harvesting cost})^2$	0.003*	(0.002)
$(\ln \text{land preparation cost})^2$	0.012	(0.028)
$(\ln \text{seed cost})^2$	0.007***	(0.002)
$(\ln \text{other costs})^2$	0.006***	(0.001)
$(\ln \text{laborer})^2$	0.007**	(0.003)
ln rice land * ln fertilizer cost	0.001	(0.001)
ln rice land * ln pesticide cost	0.000	(0.000)
ln rice land * ln harvesting cost	-0.000	(0.001)
ln rice land * ln land preparation cost	-0.011*	(0.006)
ln rice land * ln seed cost	-0.001	(0.001)
ln rice land * ln other costs	0.000	(0.001)
ln rice land * ln laborer	0.002	(0.002)
ln fertilizer cost * ln pesticide cost	0.000	(0.000)
ln fertilizer cost * ln harvesting cost	-0.000	(0.000)
ln fertilizer cost * ln land preparation cost	-0.002	(0.002)
ln fertilizer cost * ln seed cost	-0.001***	(0.000)
ln fertilizer cost * ln other costs	-0.000*	(0.000)
ln fertilizer cost * ln laborer	-0.001*	(0.000)
ln pesticide cost * ln harvesting cost	-0.000	(0.001)
ln pesticide cost * ln land preparation cost	-0.002	(0.002)
ln pesticide cost * ln seed cost	0.000	(0.000)
ln pesticide cost * ln other costs	0.000	(0.000)
ln pesticide cost * ln laborer	-0.001	(0.001)
ln harvesting cost * ln land preparation cost	0.008	(0.006)
ln harvesting cost * ln seed costs	0.001*	(0.001)
ln harvesting cost * ln other costs	-0.000	(0.001)
ln harvesting cost * ln laborer	-0.000	(0.003)
ln land preparation cost * ln seed cost	0.005**	(0.002)
ln land preparation cost * ln other costs	-0.003	(0.002)
ln land preparation cost * ln laborer	-0.004	(0.005)
ln seed cost * ln other costs	-0.000	(0.000)
ln seed cost * ln laborer	-0.000	(0.002)
ln other cost * ln laborer	-0.000	(0.001)
Constant	7.526***	(0.023)
No. of observations	3000	
Prob. > Chi^2	0.0000	
Log simulated-likelihood	1561.56	
Test constant return to scale (p-value)	0.245	

*Robust standard errors clustered at village level in parentheses; *** p<0.01, ** p<0.05, * p<0.1; as input variables are normalized by their respective means, coefficients on the first order term can be read directly as elasticity at means*

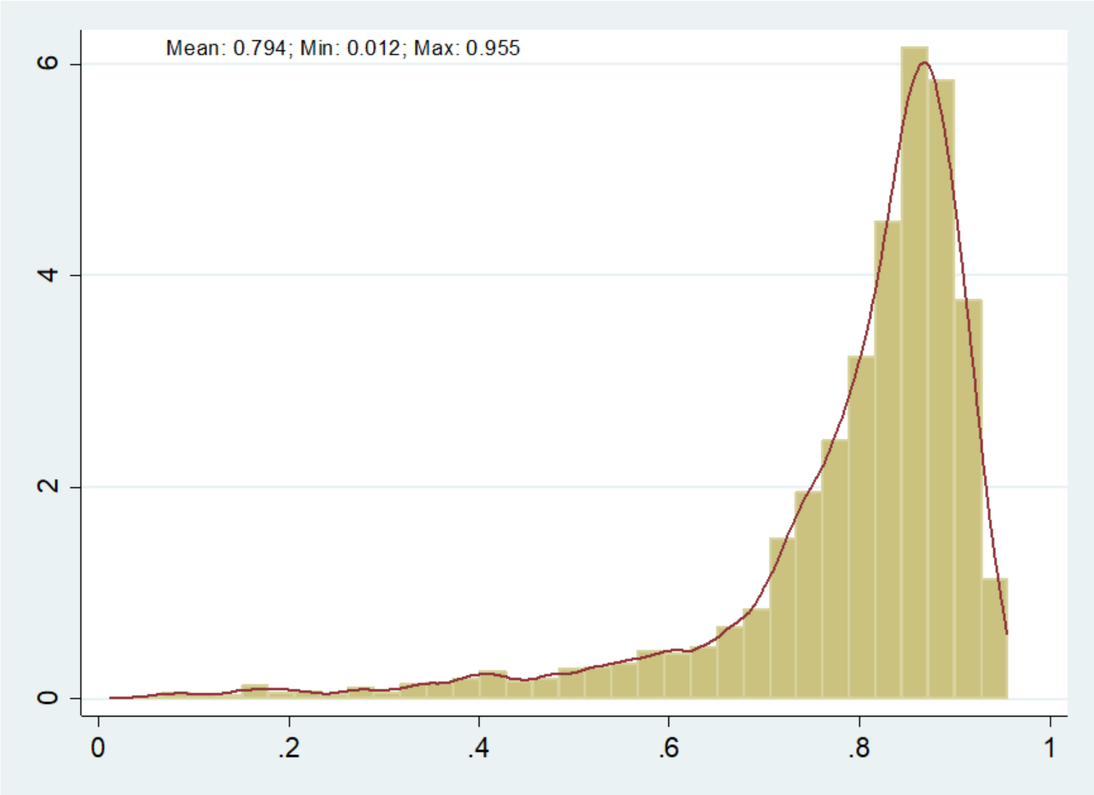

Figure 3. Estimated production efficiency scores and distribution

Table 4 shows the estimated coefficients and standard errors of the inefficiency model. In particular, column 1 and column 3 show the estimated coefficients, whereas robust standard errors are given in columns 2 and 4. The difference between the specifications in column 1 and column 3 is that in the latter column, we disaggregate the explanatory variable of access to credit into two variables of access to formal credit and access to informal credit.

Table 4. Determinants of rice production inefficiency

	Without distinguishing between credit sources		Distinguishing between credit sources	
	Coefficient	Robust SE	Coefficient	Robust SE
	(1)	(2)	(3)	(4)
informal credit			-0.056	(0.153)
formal credit			-0.006	(0.132)
credit	-0.030	(0.132)		
weather shock	0.559***	(0.182)	0.560***	(0.181)
health shock	-0.003	(0.136)	0.007	(0.138)
market shock	-0.241	(0.328)	-0.232	(0.335)
remittance	-0.000	(0.000)	-0.000	(0.000)
household size	0.063	(0.068)	0.062	(0.069)
child share	0.617	(0.546)	0.636	(0.543)
age head	0.000	(0.006)	0.001	(0.006)
education head	-0.050**	(0.022)	-0.048**	(0.022)
ethnic minority	1.286***	(0.305)	1.316***	(0.312)
phone	-0.037	(0.076)	-0.037	(0.076)
tractor	-0.190*	(0.103)	-0.190*	(0.104)
livestock	-0.000**	(0.000)	-0.000**	(0.000)
motorbike	0.005	(0.123)	0.012	(0.122)
owned farm land	0.126	(0.095)	0.138	(0.095)
farm land fragmentation	0.328***	(0.119)	0.327***	(0.120)
migration	0.286*	(0.154)	0.291*	(0.155)
non-farm employment	0.118	(0.158)	0.119	(0.157)
2010	-0.592***	(0.205)	-0.592***	(0.204)
2013	-0.125	(0.159)	-0.113	(0.159)
Hatinh	1.065**	(0.447)	1.084**	(0.469)
Hue	0.900***	(0.306)	0.959***	(0.321)
weather shock (mean for CRE)	0.635**	(0.265)	0.593	(0.372)
health shock (mean for CRE)	0.074	(0.319)	0.724***	(0.251)
market shock (mean for CRE)	0.212	(0.322)	0.072	(0.317)
credit (mean for CRE)	0.080	(0.706)		
informal credit (mean for CRE)			0.156	(0.330)
formal credit (mean for CRE)			0.010	(0.697)
remittance (mean for CRE)	0.000	(0.000)	0.000	(0.000)
household size (mean for CRE)	-0.041	(0.093)	-0.044	(0.097)
child share (mean for CRE)	-0.739	(0.677)	-0.737	(0.688)
phone(mean for CRE)	-0.080	(0.160)	-0.093	(0.162)
farm machinery (mean for CRE)	0.496*	(0.295)	0.480*	(0.287)
livestock (mean for CRE)	0.000	(0.000)	0.000	(0.000)
motorbike (mean for CRE)	-0.439**	(0.210)	-0.447**	(0.213)
owned farm land (mean for CRE)	-0.038	(0.156)	-0.051	(0.154)
farm land fragmentation (mean for CRE)	-0.705	(0.484)	-0.671	(0.479)
migration (mean for CRE)	0.013	(0.253)	-0.012	(0.259)
non-farm employment (mean for CRE)	-0.151	(0.263)	-0.156	(0.265)
Constant	-3.384***	(0.577)	-3.502***	(0.569)
No. of observations	3000		3000	
Prob. > Chi^2	0.000		0.000	
Log simulated-likelihood	-1572.602		-1568.665	

*Robust standard errors clustered at village level in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

With respect to the impact of shocks, results in both columns 1 and 3 show that weather shocks are positively and significantly associated with production inefficiency of rice farmers, whereas the impact of health shocks and market shocks is insignificant. This is reasonable as climate calamities are the most common shocks in our studied area (see Table 1). In addition, weather shocks might severely reduce farm efficiency as these events not only cause crop losses but also increase the expenditure for planting and growing crops. This is also consistent with Mishra et al. (2015; 2018) who find that extreme weather events are major sources of the inefficiency of rice production. Regarding access to credit, we do not find a significant impact of credit on farm inefficiency. For other household characteristics, households with higher education tend to be more efficient in farming activities. This is reasonable as these farmers education might be more able to effectively manage information related to markets, climate, production and technologies (Ebers et al., 2017; Nguyen et al., 2018). In addition, our findings show that the number of tractors, representing the level of farm mechanization, is negatively associated with production inefficiency. This makes sense as farm mechanization will significantly improve agricultural production by facilitating timeliness and quality of cultivation, relieving the burden of labor shortages, and reducing harvest losses and expenses for land preparation and harvesting operations (World Bank, 2009). Furthermore, our results show that the value of livestock is negatively associated with rice production inefficiency. An explanation is that rice farming activities in Vietnam still highly rely on draught animal power and the waste from livestock is also an important source of fertilizer for cropland (Do et al., 2019). Our results also indicate that land fragmentation and the migration of household members are major sources of the inefficiency of rice production. This makes sense as the shortage of household labor may cause detrimental effects on farming activities (Sauer et al, 2015). Huy and Nguyen (2019) also find that land fragmentation is significantly and positively associated with farm inefficiency in Vietnam. This is reasonable as land fragmentation increases production costs and discourages farmers from adopting innovations and modern technologies (Rahman and Rahman, 2009; Di

Falco et al., 2010). Furthermore, our results reveal that ethnic minority households appear to be less efficient than ethnic majority households. An explanation is that the ethnic minority generally has low levels of education and possesses fewer productive assets than the majority (Nguyen et al., 2020a). This is in line with van de Walle and Gunewardena (2001) and Baulch et al. (2012), who report that the ethnic minority in Vietnam generally has a lower return on productive assets than the ethnic majority.

Table 5. Effect of shocks on rice production inefficiency and the mitigating effects of credit

	Without distinguishing between credit sources		Distinguishing between credit sources	
	Coefficient	Robust SE	Coefficient	Robust SE
	(1)	(2)	(3)	(4)
credit*weather shock	-0.479**	(0.240)		
credit*health shock	-0.102	(0.244)		
credit*market shock	0.210	(0.568)		
informal credit*weather shock			-0.593**	(0.231)
informal credit*health shock			-0.379	(0.278)
informal credit*market shock			0.792	(0.485)
formal credit*weather shock			0.043	(0.260)
formal credit*health shock			0.254	(0.240)
formal credit*market shock			-0.505	(0.460)
informal credit			0.192	(0.183)
formal credit			-0.051	(0.168)
credit	0.129	(0.151)		
weather shock	0.787***	(0.187)	0.695***	(0.186)
health shock	0.031	(0.183)	0.008	(0.176)
market shock	-0.674	(0.534)	-0.680	(0.485)
control variables	yes	yes	yes	yes
No. of observations	3000		3000	
Prob. > Chi^2	0.000		0.000	
Log simulated-likelihood	-1569.678		-1561.56	

*Robust standard errors clustered at village level in parentheses; *** p<0.01, ** p<0.05, * p<0.1, see full results in Appendix 6*

To examine the role of credit in mitigating the negative effects of shocks, the interactions between credit and shocks are included in estimating rice production efficiency as shown in Table 5. The coefficient of the interaction between credit and weather shocks in column 1 is negatively and significantly correlated with the inefficiency. This reveals that the impacts of weather shocks on rice production efficiency are less severe in the group of households with access to credit, implying the important role of credit in mitigating the negative impact of weather shocks. This is consistent with Becchetti and Castriota (2011) who argue that households in developing countries generally lack self-insurance instruments such as savings and accumulated assets; therefore, borrowing is an important recovery instrument against natural catastrophes. Arouri et al. (2015) also claim that households with access to credit are more resilient to extreme weather events. Access to credit could satisfy their urgent demands for inputs such as irrigation, laborers, or fertilizers in times of crisis, therefore ensuring the continuity of the production process and enabling them to recover from shocks. In addition, the availability of credit also discourages farmers from using shock-coping strategies that are harmful to their agricultural production such as depleting productive assets or selling agricultural land (Isoto et al., 2017). In column 3, we also disaggregate credit into formal and informal sources. The results show that the interaction between informal credit and weather shocks is significant and negative. An explanation is that informal credit is generally more suitable for urgent purposes such as response to shocks than formal loans. Formal credit often requires complicated application procedures and high collateral ratio, whereas informal credit may be easier to access and available on short notice (see Barslund and Tarp, 2008). This is consistent with results in Appendix A5, in which we apply a simultaneous probit model and reveal that households are likely to borrow from informal sources in response to weather shocks, market shocks, and health shocks.

5. Conclusion

Rice is one of the most important crops in the developing world as it is the staple food and primary source of income for billions of people. Therefore, an improved understanding of the underlying factors of rice production efficiency is important to enhance the livelihoods of farmers and to ensure global food security for a growing population. Given that farmers in Vietnam often suffer from shocks and financial capital constraints, our study uses a panel dataset of 1000 Vietnamese farmers, collected in 2010, 2013, and 2016, to (i) investigate the impact of credit and shocks (weather shocks, health shocks, and market shocks) on rice production efficiency, and to (ii) examine whether credit plays a role in mitigating the impact of shocks on rice production efficiency.

Our results reveal that the mean production efficiency score of sampled farmers is 0.8, representing a significant gap of 20 per cent between the frontier and actual rice production. This indicates that farmers could significantly increase their outputs with existing technology and resources. In addition, our findings reveal that weather shocks are major sources of production inefficiency. Access to credit is found to play a significant role in mitigating the negative impact of weather shocks on production efficiency. In addition, households with higher education levels appear to be more efficient in farming activities. Livestock farming and farm mechanization are also found being positively correlated with rice production efficiency. Meanwhile, land fragmentation and the migration of household members are shown to have negative effects on rice production efficiency. Furthermore, our results show that ethnic minority households appear to be less efficient in rice production than the majority.

Our results also provide several important recommendations to the government and policymakers. First, it is essential to provide more assistance and support to farmers in mitigating the severe effects of weather shocks. In particular, the promotion of credit markets should be an important instrument to mitigate these negative impacts. In addition, the combination of crop farming and livestock rearing is suggested to enhance the efficiency of rice production. Promoting farm mechanization, land defragmentation and rural education should be also given a high priority. Furthermore, the government should have more assistance programs to support ethnic minority farmers to improve their production efficiency.

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Appendices

A1. Hypothesis test for stochastic frontier model

	Likelihood ratio test $\lambda = -2\left[\log L(\widehat{\Omega}_{H0}) - L(\widehat{\Omega}_{H1})\right]$	Degrees of freedom	P-value
Model 1:			
Choice of functional form (Cobb-Douglas vs Translog) H0: Cobb-Douglas is more appropriate	340.488	36	0.000
Inefficiencies are not stochastic H0: $\gamma = 0$	402.564	1	0.000
No inefficiency effects H0: $\beta_1 = \beta_2 = \cdots \beta_n = 0$	241.134	33	0.000
Model 2:			
Choice of functional form (Cobb-Douglas vs Translog) H0: Cobb-Douglas is more appropriate	341.32	36	0.000
Inefficiencies are not stochastic H0: $\gamma = 0$	661.772	1	0.000
No inefficiency effects H0: $\beta_1 = \beta_2 = \cdots \beta_n = 0$	249.381	35	0.000
Model 3:			
Choice of functional form (Cobb-Douglas vs Translog) H0: Cobb-Douglas is more appropriate	341.744	36	0.000
Inefficiencies are not stochastic H0: $\gamma = 0$	661.772	1	0.000
No inefficiency effects H0: $\beta_1 = \beta_2 = \cdots \beta_n = 0$	246.609	35	0.000
Model 4:			
Choice of functional form (Cobb-Douglas vs Translog) H0: Cobb-Douglas is more appropriate	343.441	36	0.000
Inefficiencies are not stochastic H0: $\gamma = 0$	661.772	1	0.000
No inefficiency effects H0: $\beta_1 = \beta_2 = \cdots \beta_n = 0$	259.208	37	0.000

$L(\widehat{\Omega}_{H0})$ is the log likelihood of constrained models under the null hypothesis, and $L(\widehat{\Omega}_{H1})$ is the log likelihood of the alternative hypothesis in Table 5; p-value is taken from Kodde and Palm (1986).

A2. Name and definition of explanatory variables

Name	Scale	Definition
rice land	ha	rice harvested land area
fertilizer cost	PPP$	total expenditure on fertilizer
pesticide cost	PPP$	total expenditure on pesticides, herbicide, insecticide, fungicides and snail killers
harvesting cost	PPP$	total expenditure on harvesting and threshing
land preparation cost	PPP$	total expenditure on land preparation
seed cost	PPP$	total expenditure on seeds, seedlings and planting
other cost	PPP$	total expenditure on weeding, irrigation and other activities
laborer	labor	total household's members with main occupation on own farm
formal credit	(yes=0, no=1)	Household borrowed from formal sources (banks, credit organizations) in the last 12 months
informal credit	(yes=0, no=1)	Household borrowed from informal sources (friends, relatives, money lenders and others) in the last 12 months
credit	(yes=0, no=1)	Household borrowed in the last 12 months
weather shock	(yes=0, no=1)	Household suffered weather shocks in the last 12 months
health shock	(yes=0, no=1)	Household suffered health shocks in the last 12 months
market shock	(yes=0, no=1)	Household suffered market shocks in the last 12 months
remittance	PPP$	Value of money and gift received from friends, relatives and migrant members in the last 12 months
household size	people	total household members
child share	proportion	share of household's members under 15 years
age head	years	age of household head
education head	years	number of school years of household head
ethnic minority	(yes=0, no=1)	household belongs to ethnic minority groups
phone	number	number of phones of household
tractor	number	number of tractors of household
livestock	PPP$	value of livestock that household owns
motorbike	number	number of motorbikes of household
owned farm land	ha	total area of farm land that household owns
farm land fragmentation	plots	number of farm plots of less than 0.02 ha
migration	(yes=0, no=1)	household has a member staying in the household for less than 180 days in the surveyed year
non-farm employment	(yes=0, no=1)	Household has a member permanently employed in non-agriculture or having non-farm own business
2010	(yes=0, no=1)	The survey year is 2010
2013	(yes=0, no=1)	The survey year is 2013
Hatinh	(yes=0, no=1)	The surveyed province is Ha Tinh
Hue	(yes=0, no=1)	the surveyed province is Thua Thien Hue

A3. Determinants of rice production inefficiency (simultaneously estimated with Cobb-Douglas Frontier Production Function)

	(1)	(2)	(3)	(4)
credit*weather shock	-0.480*	(0.273)		
credit*health shock	0.107	(0.245)		
credit*market shock	0.621	(0.561)		
informal credit*weather shock			-0.677***	(0.260)
informal credit*health shock			-0.237	(0.307)
informal credit*market shock			0.826	(0.506)
formal credit*weather shock			0.136	(0.290)
formal credit*health shock			0.298	(0.247)
formal credit*market shock			-0.149	(0.525)
informal credit			0.216	(0.204)
formal credit			-0.068	(0.176)
credit	0.099	(0.163)		
weather shock	0.686***	(0.198)	0.586***	(0.197)
health shock	-0.117	(0.196)	-0.096	(0.184)
market shock	-0.390	(0.570)	-0.273	(0.503)
remittance	-0.000	(0.000)	-0.000	(0.000)
household size	0.035	(0.070)	0.038	(0.070)
child share	0.584	(0.564)	0.551	(0.562)
age head	0.001	(0.006)	0.001	(0.006)
education head	-0.051**	(0.023)	-0.053**	(0.023)
ethnic minority	1.599***	(0.344)	1.647***	(0.344)
phone	-0.033	(0.077)	-0.029	(0.077)
tractor	-0.230**	(0.104)	-0.196*	(0.106)
livestock	-0.000**	(0.000)	-0.000**	(0.000)
motorbike	0.040	(0.134)	0.039	(0.135)
owned farm land	0.151	(0.104)	0.150	(0.103)
farm land fragmentation	0.293**	(0.126)	0.321**	(0.127)
migration	0.253*	(0.153)	0.285*	(0.154)
non-farm employment	0.160	(0.166)	0.181	(0.164)
2010	-0.435**	(0.200)	-0.440**	(0.202)
2013	0.250	(0.158)	0.252	(0.155)
Hatinh	1.625***	(0.483)	1.668***	(0.497)
Hue	1.067***	(0.348)	1.118***	(0.357)
weather shock (mean for CRE)	0.477*	(0.282)	0.507	(0.393)
health shock (mean for CRE)	0.178	(0.324)	0.566**	(0.278)
market shock (mean for CRE)	0.268	(0.319)	0.184	(0.315)
credit (mean for CRE)	-0.203	(0.721)		
informal credit (mean for CRE)			0.222	(0.331)
formal credit (mean for CRE)			-0.257	(0.692)
remittance (mean for CRE)	0.000	(0.000)	0.000	(0.000)
household size (mean for CRE)	-0.031	(0.091)	-0.046	(0.096)
child share (mean for CRE)	-0.655	(0.717)	-0.592	(0.727)
phone(mean for CRE)	-0.053	(0.164)	-0.080	(0.163)
farm machinery (mean for CRE)	0.488	(0.297)	0.405	(0.281)
livestock (mean for CRE)	0.000	(0.000)	0.000	(0.000)
motorbike (mean for CRE)	-0.513**	(0.217)	-0.497**	(0.222)
owned farm land (mean for CRE)	-0.130	(0.161)	-0.121	(0.160)
farm land fragmentation (mean for CRE)	-0.665	(0.454)	-0.643	(0.447)
migration (mean for CRE)	-0.015	(0.255)	-0.061	(0.260)
non-farm employment (mean for CRE)	-0.123	(0.274)	-0.126	(0.271)
Constant	-3.738***	(0.656)	-3.804***	(0.645)
No. of observations	3000		3000	
Prob. > Chi^2	0.000		0.000	
Log simulated-likelihood	-1740.0443		-1733.549	

*Robust standard errors clustered at village level in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

A4. Determinants of rice production inefficiency (simultaneously estimated with Translog Frontier Production Function, total rice outputs (in tons) is the main outcome)

	(1)	(2)	(3)	(4)
credit*weather shock	-0.479**	(0.240)		
credit*health shock	-0.102	(0.244)		
credit*market shock	0.210	(0.568)		
informal credit*weather shock			-0.593**	(0.231)
informal credit*health shock			-0.379	(0.278)
informal credit*market shock			0.792	(0.485)
formal credit*weather shock			0.043	(0.260)
formal credit*health shock			0.254	(0.240)
formal credit*market shock			-0.505	(0.460)
informal credit			0.192	(0.183)
formal credit			-0.051	(0.168)
credit	0.129	(0.151)		
weather shock	0.787***	(0.187)	0.695***	(0.186)
health shock	0.031	(0.183)	0.008	(0.176)
market shock	-0.674	(0.534)	-0.680	(0.485)
remittance	-0.000	(0.000)	-0.000	(0.000)
household size	0.082	(0.062)	0.085	(0.062)
child share	0.477	(0.493)	0.444	(0.493)
age head	0.000	(0.005)	0.001	(0.005)
education head	-0.037*	(0.019)	-0.037*	(0.019)
ethnic minority	1.337***	(0.278)	1.389***	(0.282)
phone	0.010	(0.071)	0.017	(0.071)
tractor	-0.225**	(0.099)	-0.186*	(0.098)
livestock	-0.000*	(0.000)	-0.000*	(0.000)
motorbike	-0.194	(0.120)	-0.198	(0.123)
owned farm land	0.205**	(0.091)	0.208**	(0.090)
farm land fragmentation	0.322**	(0.130)	0.348***	(0.132)
migration	0.072	(0.137)	0.088	(0.137)
non-farm employment	0.158	(0.147)	0.171	(0.150)
2010	0.382**	(0.189)	0.388**	(0.186)
2013	0.380***	(0.141)	0.398***	(0.136)
Hatinh	1.209***	(0.376)	1.242***	(0.393)
Hue	1.043***	(0.273)	1.078***	(0.282)
weather shock (mean for CRE)	0.665***	(0.253)	0.597*	(0.345)
health shock (mean for CRE)	0.015	(0.297)	0.706***	(0.242)
market shock (mean for CRE)	0.315	(0.290)	0.019	(0.293)
credit (mean for CRE)	0.278	(0.620)		
informal credit (mean for CRE)			0.269	(0.300)
formal credit (mean for CRE)			0.245	(0.599)
remittance (mean for CRE)	-0.000	(0.000)	-0.000	(0.000)
household size (mean for CRE)	-0.071	(0.078)	-0.080	(0.082)
child share (mean for CRE)	-0.790	(0.631)	-0.741	(0.646)
phone(mean for CRE)	-0.133	(0.147)	-0.162	(0.147)
farm machinery (mean for CRE)	0.431	(0.289)	0.330	(0.266)
livestock (mean for CRE)	0.000	(0.000)	0.000	(0.000)
motorbike (mean for CRE)	-0.082	(0.179)	-0.051	(0.183)
owned farm land (mean for CRE)	-0.133	(0.138)	-0.137	(0.138)
farm land fragmentation (mean for CRE)	-0.755*	(0.401)	-0.720*	(0.400)
migration (mean for CRE)	0.215	(0.237)	0.180	(0.238)
non-farm employment (mean for CRE)	-0.249	(0.228)	-0.249	(0.228)
Constant	-4.025***	(0.523)	-4.076***	(0.515)
No. of observations		3000		3000
Prob. > Chi^2		0.000		0.000
Log simulated-likelihood		-1176.9059		-1168.3571

*Robust standard errors clustered at village level in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

A5. Factors affecting household access to credit sources

	Simultaneous probit model			
	Access to informal credit		Access to formal credit	
	Coefficient	Std.	Coefficient	Std.
weather shock	0.149***	(0.056)	0.027	(0.056)
health shock	0.253***	(0.068)	0.114**	(0.058)
market shock	0.252**	(0.119)	0.072	(0.113)
remittance	-0.000**	(0.000)	-0.000**	(0.000)
household size	0.055**	(0.023)	0.017	(0.018)
child share	-0.001	(0.161)	-0.224	(0.139)
age head	-0.011***	(0.003)	-0.007**	(0.003)
education head	-0.032***	(0.008)	0.010	(0.009)
ethnic minority	-0.141	(0.110)	-0.041	(0.089)
phone	0.004	(0.025)	0.034	(0.023)
tractor	0.065	(0.052)	0.108**	(0.048)
livestock	-0.000**	(0.000)	0.000*	(0.000)
motorbike	-0.059	(0.036)	0.031	(0.035)
owned farm land	0.059	(0.040)	0.048	(0.032)
farm land fragmentation	0.058	(0.055)	-0.048	(0.054)
migration	0.053	(0.059)	0.140**	(0.057)
non-farm employment	-0.168***	(0.060)	0.140***	(0.053)
2010	-0.298***	(0.074)	0.086	(0.077)
2013	-0.398***	(0.066)	-0.034	(0.059)
constant	0.134	(0.227)	-0.553***	(0.214)
No of observations	3000			
Wald $Chi^2(38)$	224.62			
Prob. > chi^2	0.000			

*Robust standard errors clustered at village level in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

A6. Effect of shocks on rice production inefficiency and the mitigating effects of credit

	(1)	(2)	(3)	(4)
credit*weather shock	-0.479**	(0.240)		
credit*health shock	-0.102	(0.244)		
credit*market shock	0.210	(0.568)		
informal credit*weather shock			-0.593**	(0.231)
informal credit*health shock			-0.379	(0.278)
informal credit*market shock			0.792	(0.485)
formal credit*weather shock			0.043	(0.260)
formal credit*health shock			0.254	(0.240)
formal credit*market shock			-0.505	(0.460)
informal credit			0.192	(0.183)
formal credit			-0.051	(0.168)
credit	0.129	(0.151)		
weather shock	0.787***	(0.187)	0.695***	(0.186)
health shock	0.031	(0.183)	0.008	(0.176)
market shock	-0.674	(0.534)	-0.680	(0.485)
remittance	-0.000	(0.000)	-0.000	(0.000)
household size	0.082	(0.062)	0.085	(0.062)
child share	0.477	(0.493)	0.444	(0.493)
age head	0.000	(0.005)	0.001	(0.005)
education head	-0.037*	(0.019)	-0.037*	(0.019)
ethnic minority	1.337***	(0.278)	1.389***	(0.282)
phone	0.010	(0.071)	0.017	(0.071)
tractor	-0.225**	(0.099)	-0.186*	(0.098)
livestock	-0.000*	(0.000)	-0.000*	(0.000)
motorbike	-0.194	(0.120)	-0.198	(0.123)
owned farm land	0.205**	(0.091)	0.208**	(0.090)
farm land fragmentation	0.322**	(0.130)	0.348***	(0.132)
migration	0.072	(0.137)	0.088	(0.137)
non-farm employment	0.158	(0.147)	0.171	(0.150)
2010	0.382**	(0.189)	0.388**	(0.186)
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Hatinh	1.209***	(0.376)	1.242***	(0.393)
Hue	1.043***	(0.273)	1.078***	(0.282)
weather shock (mean for CRE)	0.665***	(0.253)	0.597*	(0.345)
health shock (mean for CRE)	0.015	(0.297)	0.706***	(0.242)
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remittance (mean for CRE)	-0.000	(0.000)	-0.000	(0.000)
household size (mean for CRE)	-0.071	(0.078)	-0.080	(0.082)
child share (mean for CRE)	-0.790	(0.631)	-0.741	(0.646)
phone(mean for CRE)	-0.133	(0.147)	-0.162	(0.147)
farm machinery (mean for CRE)	0.431	(0.289)	0.330	(0.266)
livestock (mean for CRE)	0.000	(0.000)	0.000	(0.000)
motorbike (mean for CRE)	-0.082	(0.179)	-0.051	(0.183)
owned farm land (mean for CRE)	-0.133	(0.138)	-0.137	(0.138)
farm land fragmentation (mean for CRE)	-0.755*	(0.401)	-0.720*	(0.400)
migration (mean for CRE)	0.215	(0.237)	0.180	(0.238)
non-farm employment (mean for CRE)	-0.249	(0.228)	-0.249	(0.228)
Constant	-4.025***	(0.523)	-4.076***	(0.515)
No. of observations	3000		3000	
Prob. > Chi^2	0.000		0.000	
Log simulated-likelihood	-1569.678		-1561.56	

*Robust standard errors clustered at village level in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

Chapter 5. Shocks, Agricultural Productivity, and Natural Resource Extraction in Rural Southeast Asia

Abstract

Natural resources are depleting at an alarming rate, causing severe threats to the sustainable development in many developing countries. Given an ambiguous relationship between shocks, agricultural productivity, and natural resource extraction, we use a dataset of about 4200 rural households surveyed in four Southeast Asian countries (Cambodia, Laos, Thailand, and Vietnam) to investigate the impact of shocks and agricultural productivity on natural resource extraction by rural households. Our results show that weather shocks and market shocks push households to extract more natural resources. An increased agricultural productivity, however, discourages natural resource extraction. In addition, our results show that low education, poor electricity access and a lack of entrepreneurial activities in the village are positively associated with natural resource extraction. We suggest that measures enhancing agricultural productivity should be prioritized, and more assistance and support to farmers for mitigating the severe effect of weather shocks and market shocks should be provided. Furthermore, rural education, rural electrification, and the development of local enterprises should be promoted.

1. Introduction

Natural resource extraction is one of the major livelihood strategies of rural households in many developing countries (López-Feldman & Chávez, 2017; Wunder et al., 2014). It provides a wide range of products such as food, medicine, fuel, and construction materials for fulfilling households' subsistence needs and generating cash income (Angelsen et al., 2014). In addition, it also plays an important role as safety net in response to severe income shocks such as climate calamities or illness (Angelsen et al., 2014). However, natural resource overexploitation is happening at an alarming rate. Natural forests had been declining by approximately 6.5 million hectares (ha) per year during the period from 2010 to 2015 and the population of vertebrates had been decreasing by about 60 percent (%) between 1970 and 2014 (FAO, 2016; WWF, 2018). Many of these degraded ecosystems might not be able to fully recover, causing long-lasting consequences for the future provision of natural resources and ecosystem services (Lampert, 2019). Therefore, identifying the factors affecting households' decision to extract natural resources is essential to provide useful information for policymakers and practitioners to design effective programs for environmental conservation.

Another major livelihood strategy of rural households in developing countries is agricultural production. It is the main source of employment and income for at least 30% of the population in low- and middle-income countries (World Bank, 2020). Of this percentage, small-scale farmers make up the majority, approximately 80% of the farming population (Lowder et al., 2016). Their conventional farming methods often rely on using cows as draught power, indigenous seeds, simple equipment, and are highly dependent on weather conditions (Boonsrirat, 2014; Nguyen et al., 2020). Therefore, their productivity is relatively moderate and might not be able to ensure adequate food and sufficient income for farmers (Nguyen et al., 2018a). Consequently, other occupations such as natural resource extraction are also needed (Walelign, 2017). The relationship between agricultural production and natural resource extraction deserves special attention but has been investigated only in a few studies with mixed results. On the one hand, it is argued that improving agricultural productivity motivates farmers to convert more forests to farmland or enables them to access modern technologies accelerating their extraction activities. On the other hand, studies show that increasing agricultural productivity enhances the opportunity cost of extraction activities, thus reducing natural resource extraction (Illukpitiya and Yanagida, 2010; Nguyen et al., 2018b).

Rural households in developing countries frequently suffer from different types of shocks. Due to the lack of insurance mechanisms, shocks might cause severe impacts on household welfare, pushing them into food insecurity and poverty. In addition, to smooth their current consumption, rural households may adopt harmful coping strategies, which may have severe consequences on the long-term welfare of the households as well as of the society such as selling productive assets or over-exploitation of natural resources. Obviously, the choice of shock coping strategies depends on the type of shocks, household characteristics, the availability of coping strategies as well as the characteristics of local markets (Nguyen et al., 2020; Wunder et al., 2014). Those shocks that reduce labour availability (e.g. illness or death) may dissuade households from using labour-intensive responses, such as extracting natural resources. Meanwhile, households may rely more on natural resources as safety nets when they face covariate shocks (e.g. weather shocks or market shocks) because other coping strategies that depend on the community (e.g., assistance from friends, borrowing money) may not be available.

Against this background, our study uses a large dataset collected from more than 4200 rural households in Southeast Asia region (Cambodia, Lao, Thailand, and Vietnam) (i) to examine the impact of shocks, including health shocks, weather shocks, and market shocks, on agricultural productivity, and (ii) to investigate the impact of agricultural productivity and of shocks on natural resource extraction. These Southeast Asian countries are suitable study sites for our research as (i) this region is rich in natural resources but among the major hotspots of natural resource degradation, (ii) it also has a large share of the population working in the agricultural sector and relying on natural resource extraction, (iii) households in this region are highly vulnerable to shocks. Our study makes some important contributions to the economics literature and provides useful information for policymakers. First, we enrich our understanding regarding the impact of agricultural productivity on natural resource extraction, which has received little attention in the previous literature with ambiguous findings. Second, we deal with endogeneity problems in estimating the impact of agricultural productivity on natural resource extraction. Third, while previous studies on natural resource extraction are often site-specific, which makes the generalization of the research findings difficult; our study is conducted in four different countries. Fourth, our study quantifies the effects of different types of shocks, whereas previous studies tend to focus on a single type of shock or combined measures of shock.

The rest of the paper is structured as follows. Section 2 presents the literature review. Study sites, data sources, and methodologies are described in Section 3. Section 4 presents the results and discusses the findings. Section 5 concludes with policy implications.

2. Literature Review

Natural resource extraction is among the crucial livelihood strategies of rural households in many developing countries (López-Feldman & Chávez, 2017; Wunder et al., 2014). This refers to extraction activities from non-cultivated sources such as natural forests, rivers, lakes, non-forest wildlands, fallows, but also wild animals and wild plants in cultivated areas (Angelsen et al., 2014; Nguyen et al., 2018a). Previous literature has shown that natural resources might contribute to rural livelihoods via three major channels: (i) providing a variety of products such as food, fuel, construction materials, and medicine to satisfy households' subsistence needs, (ii) providing a means of asset accumulation or a pathway out of poverty via regular cash income provision, and (iii) serving as safety nets in response to shocks or gap-filling of seasonal shortfalls (Wunder et al., 2014).

A number of studies have investigated the determinants of households' decision to extract natural resources and they commonly find that the extraction is mainly determined by household characteristics (e.g. age, asset, education, occupation), local characteristics (e.g. accessibility to markets, non-employment opportunities), and vulnerability context (e.g. shocks or risks) (Angelsen et al., 2014; Nguyen et al., 2015, Wunder et al., 2014). Particularly, McSweeney et al. (2004) show that young households with little land and few assets are more likely to rely on natural resources to cope with shocks in Honduras. Völker and Waibel (2010) find that poor households with lower education levels and suffering from shocks appear to be more involved in extraction activities in Vietnam. This is due to the fact that extracting natural resources usually requires little human or financial capital. Thus, it is a suitable option for poor households with large household sizes and extra labor force available (Neumann & Hirsch, 2000; Wunder et al. 2014). Meanwhile, households with higher education levels are less likely involved in extraction activities as they have access to more remunerative options (Fisher et al., 2010; Volker & Waibel, 2010). Local characteristics such as the accessibility to markets or the availability of alternative employment opportunities are also found to significantly correlate with natural resource extraction (Angelsen & Kaimowitz, 1999, Nguyen et al., 2020). Angelsen et al. (2014) and Nguyen et al., (2020) find that living in villages with lower degrees of market integration or far from markets could motivate households to extract more natural resources. Angelsen and Kaimowitz (1999) and Nguyen et al. (2015) find that the availability of off-farm employment opportunities will reduce the likelihood that households participate in natural resource extraction. It is explained that the availability of non-farm employment increases the opportunity costs of extraction activities, thus discouraging households from extracting natural resources.

However, few empirical studies have investigated the impact of agricultural productivity on natural resource extraction and their results are mixed. On the one hand, some studies show that improving agricultural efficiency could discourage households from extracting natural resources as it will make farming activities more profitable, therefore, positively affecting the opportunity cost of extraction activities (Illukpitiya and Yanagida, 2010). In addition, raising agricultural productivity makes farmers wealthier, allowing them to substitute market goods for forest goods (Nguyen et al., 2018b). On the other hand, it is argued that raising incomes from and returns on agricultural activities might motivate farmers to convert forests to farmland (Angelsen and Kaimowitz, 2001; Byerlee et al., 2014; Ceddia et al., 2013). In addition, an increase in returns on agricultural production could make rural households wealthier, enabling them to access modern technologies to accelerate extraction activities.

A few studies have investigated the impact of shocks on natural resource extraction, but the results vary across study sites and types of shocks. Nguyen et al. (2020) in Cambodia and Takasaki et al. (2004) in Peru show that extracting natural resources is a major coping strategy adopted by households to cope with extreme weather events. Debela et al. (2012) show that damages and losses due to market shocks are among major factors motivating households to extract more natural resources in Uganda. Using a global dataset, Babigumira et al. (2014) do not find a significant correlation between shocks and forest extraction. However, this study does not differentiate types of shocks. It is argued that households might respond differently to different types of shocks. Natural resources might play a more important role as a safety net in response to covariate shocks than to idiosyncratic shocks (Wunder et al., 2014). As covariate shocks such as extreme weather events affect most households in a community, coping strategies that depend on the community (e.g., borrowing money, receiving remittance) may become less viable because relatives, friends, and neighbors may also be negatively affected by the same shock.

3. Study Design

3.1. Study site and data sources

Our analysis is conducted in rural areas in four Southeast Asian countries, including Cambodia, Laos, Thailand, and Vietnam. This region is endowed with diverse natural resources, but also among major hotspots of natural resource degradation (Estoque et al., 2019; Stibig et al., 2014). It is reported that Southeast Asia lost about 30 million ha of forest between 1990 and 2010 and 40% of the region's biodiversity may vanish by 2100 (Estoque et al., 2019). With regard to the economic characteristics of the four surveyed countries, Thailand is overall more developed and is categorized as an upper-middle income country, Vietnam is a lower-middle income country, and Laos and Cambodia are in the group of least developed countries (United Nations, 2015). In addition, these countries are commonly characterized by a majority of people living in the rural areas and by high dependence on agriculture and natural resources (Birthal et al., 2019; Do & Park, 2019; Zhai & Zhuang, 2009). The shares of the workforce in the agricultural sector in Cambodia, Laos, Thailand, and Vietnam are approximately 40%, 70%, 30%, and 40%, respectively (Birthal et al., 2019). Furthermore, Southeast Asia is among the most vulnerable regions to climate risks with Vietnam, Thailand, Cambodia, and Laos being ranked at 9th, 13th, 19th, and 89th, respectively (Eckstein et al., 2019). It is estimated that due to global climate change, extreme weather events will occur more frequently and more severely in this region, causing a potential drop in rice yields by up to 50% by 2100 compared to 1990 levels (Prakash, 2018). This poses severe threats and challenges to ensure food security for the increasing total population that could reach over 800 million by 2050 (about 20% more than the Southeast Asian population in 2019) (Hirsch & Lottje, 2009; Birthal et al., 2019).

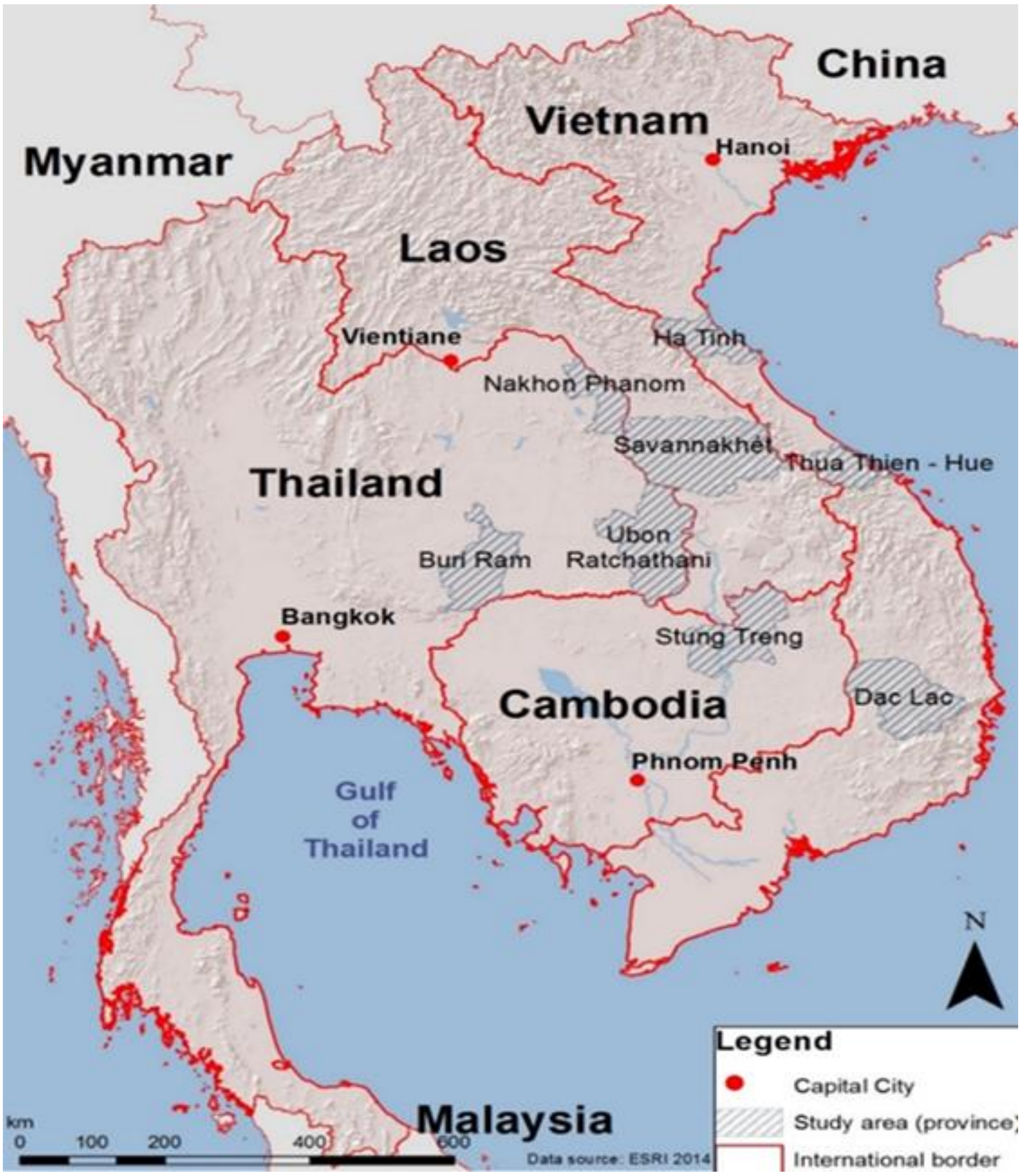

Figure 1. Map of studied sites in Cambodia, Laos, Thailand, and Vietnam

Our data were collected in 2013 in eight provinces in these four countries: Stung Treng in Cambodia; Savannakhet in Laos; and Dak Lak, Ha Tinh and Thua Thien Hue in Vietnam; Buriram, Nakhon Phanom and Ubon Ratchathani in Thailand (see Figure 1). These provinces were selected because of (i) a high incidence of poverty, (ii) their economies highly reliant on agriculture, and (iii) having rich and diverse natural resources. In Thailand and Vietnam, the survey was conducted under the project "Impact of shocks on the vulnerability to poverty: Consequences for development of emerging Southeast Asian Economies (DFG FOR 756)" funded by the German Research Foundation (Deutsche Forschungsgemeinschaft – DFG). This project aims to generate a deeper understanding of income and vulnerability to poverty in rural areas of rapidly emerging economies. Following the guidelines of the UN Department of Economic and Social Affairs (United Nations, 2005), the random sampling was undertaken based on the three-stage procedure (sub-district, villages and then household; see Povel, 2015; Nguyen et al., 2017 for detailed information of the survey). The first stage was the selection of sampled sub-districts in each province. Then, sampled villages within the chosen sub-districts were selected with a probability proportional to the size of the population. At the third stage, 10 households in each sampled village were randomly chosen. For a generalization of our findings in the Lower Mekong Basin region, similar surveys were conducted in Laos and Cambodia. The surveys were carried out in collaboration with local institutions (Development Resource Institute in Cambodia; University of Champasak in Laos; University of Ubon Ratchathani in Thailand). All enumerators were carefully selected and intensively trained before the surveys took place. Each enumerator conducted face-to-face interviews of around two hours at households' homes. Collected data from each interview was checked in multiple steps (by another enumerator, team leaders, and data typists). In case of missing or implausible data, questionnaires were sent back to the responsible enumerators for correction, either by phone or by another visit to the household.

Two types of questionnaires were used for the data collection: (1) village questionnaire and (2) household questionnaire. The village questionnaire captures villages' information on population, infrastructure, geography, and socioeconomic conditions. The household questionnaire include several sections on health, education, occupation of household members, shocks, agricultural production, natural resource extraction, income, consumption, remittances and financial transfers. The information on natural resource extraction encompasses a wide range of activities such as fishing, hunting, collecting, and logging. These income generation activities were recorded with detailed information about types of extracted products, extraction places, types of activities, extraction costs (e.g. fuel, tools, and materials), and total outputs (quantity and value). As our study mainly focuses on the impact of agricultural productivity on natural resources extraction, we exclude households not engaged in farming activities. Therefore, the final sample includes 4,213 observations with 507 observations from Laos, 503 observations from Cambodia, 1,578 from Thailand, and 1,625 observations from Vietnam.

3.2. Data description

Table 1. Household and village characteristics

	Whole Sample	Cambodia	Laos	Thailand	Vietnam
Household characteristics					
age of head	53.63	44.8	48.89	58.76	52.87
(years)	(13.68)	(13.97)	(13.36)	(12.2)	(12.94)
share of literate members	78.36	51.71	58.47	87.48	83.96
(%)	(26.91)	(30.41)	(31.66)	(18.77)	(21.96)
hhsize	4.42	5.25	5.99	4.02	4.07
(numbers)	(1.97)	(1.93)	(2.46)	(1.67)	(1.74)
share of male laborers	29.18	29.57	28.63	28.36	30.02
(%)	(20.08)	(16.05)	(15.06)	(21.58)	(21.03)
total asset per capita	1410.78	503.16	759.33	2460.32	875.79
(PPP$)	(3430.87)	(786.99)	(1234.2)	(5114.27)	(1649.13)
tractor_value	1112.23	852.95	1531.46	1966.1	232.51
(PPP$)	(4085.9)	(1679.15)	(1622.44)	(6376.4)	(752.93)
land area	1.87	3.04	2.24	2.29	0.99
(ha)	(2.12)	(3.02)	(1.89)	(2.21)	(1.24)
irrigated land area	0.3	0.26	0.07	0.14	0.53
(ha)	(0.78)	(0.96)	(0.51)	(0.68)	(0.81)
no. of land plots	3.9	2.69	2.2	3.69	5.02
(numbers)	(2.18)	(0.85)	(0.48)	(1.75)	(2.52)
share of rice-planted	62.19	47.36	55.79	83.75	47.84
area (%)	(41.39)	(44.96)	(44.65)	(30.27)	(39.62)
share of fruit-planted	6.17	23.98	7.01	2.65	3.81
area (%)	(21.27)	(40.34)	(21.59)	(13.86)	(14.93)
share of vegetable-	6.62	11.57	28.94	1.49	3.11
planted area (%)	(21.55)	(29.04)	(39.37)	(9.4)	(13.2)
share of industrial crop-	13.31	0.28	0.58	7.83	26.62
planted area (%)	(29.45)	(4.5)	(5.66)	(21.68)	(38.31)
crop income	2374.93	1762.94	926.55	1911.08	3466.68
(PPP$ per ha)	(3934.81)	(3315.77)	(1660.99)	(3468.33)	(4695.1)
crop yields	3300.78	1881.9	1131.79	2956.79	4750.74
(PPP$ per ha)	(4388.75)	(3447)	(1719.23)	(3529.2)	(5381.08)
having extracting job	55.49	81.91	84.22	48.54	45.11
(%)	(49.7)	(38.53)	(36.49)	(49.99)	(49.78)
extraction income	387.79	1876.21	664.91	85.28	134.38
(PPP$)	(1542.34)	(3853.86)	(1015.85)	(263.93)	(571.08)
Village characteristics					
share of hh with access	84.67	20.43	64.46	98.52	97.42
to electricity (%)	(33.08)	(32.71)	(42.61)	(7.73)	(11.38)
distance to market	9.51	26.96	14.63	8.88	3.12
(km)	(14.03)	(25.54)	(16.49)	(7.77)	(4.69)
having enterprises	11.99	1.19	7.69	10.01	18.58
(numbers)	(32.48)	(10.87)	(26.67)	(30.03)	(38.91)
No. of households	**4213**	**503**	**507**	**1578**	**1625**

Standard deviations are in parentheses

Table 1 illustrates household and village characteristics by countries. For demographic characteristics, households in Cambodia and Laos have larger household size, younger household heads, and lower literacy rates than in Thailand and Vietnam. On average, above 80% of the sampled rural population in Thailand and Vietnam can read and write, whereas these figures in Cambodia and Laos are less than 60%. In addition, sampled households in Thailand appear to be better off with total asset value per capita of more than 2,000 PPP$. Lower than the figure in Thailand, total asset value per capita of households in Vietnam is around 900 PPP$, but still higher than that of households in Cambodia and Laos. With regard to land and farm characteristics, households in Vietnam have the smallest land area, but the highest number of land plots. This reflects the fact that most rural farmers in Vietnam are small-scale farmers with land being highly fragmented (Huy et al., 2019). However, irrigation systems are more accessible in Vietnam than in other countries. In particular, the irrigated land area is around 0.5 ha in Vietnam, accounting for nearly 50% of total land area, whereas the figure in the other countries is less than 20%. This is in line with Birthal et al. (2019) who show that irrigation is limited to less than 20% of the cropland in most Southeast Asian countries, whereas in Vietnam above 40% of the cropland is irrigated. This might explain why the total value of crop output per hectare is highest in Vietnam. In particular, the average value of the crop yield in Vietnam is above 4,700 PPP$ per hectare, whereas these figures in Thailand, Cambodia, and Laos are approximately 3,000 PPP$, 1,800 PPP$ and 1,000 PPP$, respectively. The higher yields in Vietnam could be explained by a large share of land used for commercially industrial crops such as pepper, tomato, and coffee as well as the intensive use of fertilizer and other agro-chemicals. For natural resource extraction, households in Laos and Cambodia are more involved in extraction activities. In particular, more than 80% of households in Laos and Cambodia participate in extraction activities, whereas these figures in Thailand and Vietnam are less than 50%. With regard to village characteristics, almost all farmers in Vietnam and Thailand have access to the national electricity grids. Meanwhile, the share of farmers having access to electricity in Laos and Cambodia are 60% and 20%, respectively. In addition, off-farm employment opportunities (represented by the availability of enterprises in the villages) and the degree of integration to markets (represented by the distance to the nearest market) are also better in Vietnam and Thailand. In particular, infrastructure in rural villages in Vietnam appears most developed with the average distance to the nearest market of less than 5 km and around 20% of villages having an enterprise. In contrast, only 1% of villages in Cambodia have enterprises and the average distance from these villages to markets is more than 25 km.

Table 2. Descriptive statistics of extraction activities of rural households

	Whole sample	**Cambodia**	**Laos**	**Thailand**	**Vietnam**
Extracting places					
water (e.g. rivers, lakes)	31.79	35.59	34.01	40.4	10.21
(%)	(46.57)	(47.9)	(47.39)	(49.09)	(30.3)
forest and other lands	68.21	64.41	66	59.59	89.79
(%)	(89.86)	(69.19)	(83.34)	(85.2)	(97.12)
distance to extracting places	3.03	3.23	1.72	3.47	3.92
(km)	(6.98)	(6.91)	(3.26)	(5.82)	(11.17)
Type of extracted products					
animal products	38.42	44	47.77	42.42	12.42
(%)	(48.65)	(49.67)	(49.97)	(49.44)	(33)
wood products	24.88	24.78	2.19	11.2	79.34
(%)	(43.23)	(43.2)	(14.65)	(31.55)	(40.51)
other products (e.g. mushroom, vegetables	36.71	31.22	50.04	46.38	8.24
(%)	(48.21)	(46.37)	(50.02)	(49.89)	(27.52)
Type of activities					
Fishing	31.08	36.79	33.74	38.24	9.1
(%)	(46.29)	(48.25)	(47.3)	(48.61)	(28.78)
Hunting	7.44	7.53	14.37	3.81	3.57
(%)	(26.24)	(26.41)	(35.1)	(19.15)	(18.56)
Collecting	48.8	45.63	47.94	51.38	49.32
(%)	(49.99)	(49.84)	(49.98)	(50)	(50.03)
Logging	12.66	10.04	3.94	6.5	38.01
(%)	(33.26)	(30.07)	(19.47)	(24.66)	(48.57)
Output value and uses					
Total extraction value	385.77	1030.27	295.45	98.99	258.7
(PPP$)	(1457.2)	(2864.13)	(559.58)	(242.46)	(769.03)
Value for sales	215.25	667.79	147.89	23.12	119.13
(PPP$)	(1321.3)	(2651.6)	(510.14)	(139.13)	(669.14)
Value for consumption	170.33	363.73	148.75	75.86	139.56
(PPP$)	(356.78)	(624.55)	(215.78)	(176.87)	(215.01)
No. of activities	**4209**	**916**	**1141**	**1339**	**813**

Standard deviations are in parentheses

Table 2 provides detailed information of extraction activities including extraction locations (e.g. forest, rivers), type of products extracted (e.g. animal, wood), type of extraction activities (e.g.

fishing, logging), output value and the use of extracted products (e.g. for consumption or for cash income). Generally, forests are the most common extraction places in all surveyed countries with above 60% of all extraction activities. The distance to extraction places is farthest in Vietnam (approximately 4 km), and shortest in Laos (about 2 km). Meanwhile, the average distance to extraction places in Cambodia and Thailand are around 3 km. For types of extraction activities, the most common activity in Vietnam is collecting, whereas the second most common is logging activities. By comparison, collecting is the most common activity in Cambodia, Laos, and Thailand, whereas fishing is the second. In Vietnam, mainly wood is extracted, accounting for almost 80% of total extracted products. Meanwhile, in the other countries, wood products only account for 25% in Cambodia, 11% in Thailand, and 2% in Laos. For the value and the use of extracted products, the average output value of extraction activities is highest in Cambodia, with slightly more than 1,000 PPP$ and mainly used for sale. On the other hand, the average output value of extraction activities is lowest in Thailand amounting to around 100 PPP$ and mainly used for home consumption. The average value of extracted products in Laos and Vietnam is nearly 300 PPP$ with around a half of these values used for consumption and the other half for sale.

With regard to shocks, Figure 2 presents the shares of affected households and the average damages and losses of shocks per affected household. In particular, the line charts show that climate calamities (e.g. floods, droughts, storms) are the most common shocks, affecting more than 30% of households in all surveyed countries. Meanwhile, the share of population affected by health shocks (e.g. death, illness) is above 20%. Market shocks (e.g. increase in input prices or decrease in output price) are less common, affecting less than 10% of the households in all surveyed countries. Comparing the prevalence and severity of shocks between countries, weather shocks and health shocks are more common in Cambodia, whereas market shocks affect a larger share of households in Vietnam and Thailand. In particular, weather shocks affect around 60% of the households in Cambodia, and from 40% to 50% of the households in other countries. The share of households affected by health shocks in Cambodia is around 55%, whereas this figure in other countries is between 30% and 40%. Market shocks affect around 10% of all households in Vietnam and Thailand, whereas less than 5% of households in Cambodia and Laos are affected by market shocks. With respect to the damages and losses due to shocks, the bar charts show that weather shocks are the most severe shocks to households in Thailand and Vietnam with the average damages of around 1,100 PPP$ and 900 PPP$, respectively. In Cambodia, the most severe ones are market shocks, causing an average damage of around 800 PPP$, whereas the average damage of health shocks and weather shocks in this country amounts around 600$. In contrast, the most severe shocks in Laos are health and weather shocks, causing an average damage of around 700 PPP$, whereas the average damage of market shocks in this country is around 500$.

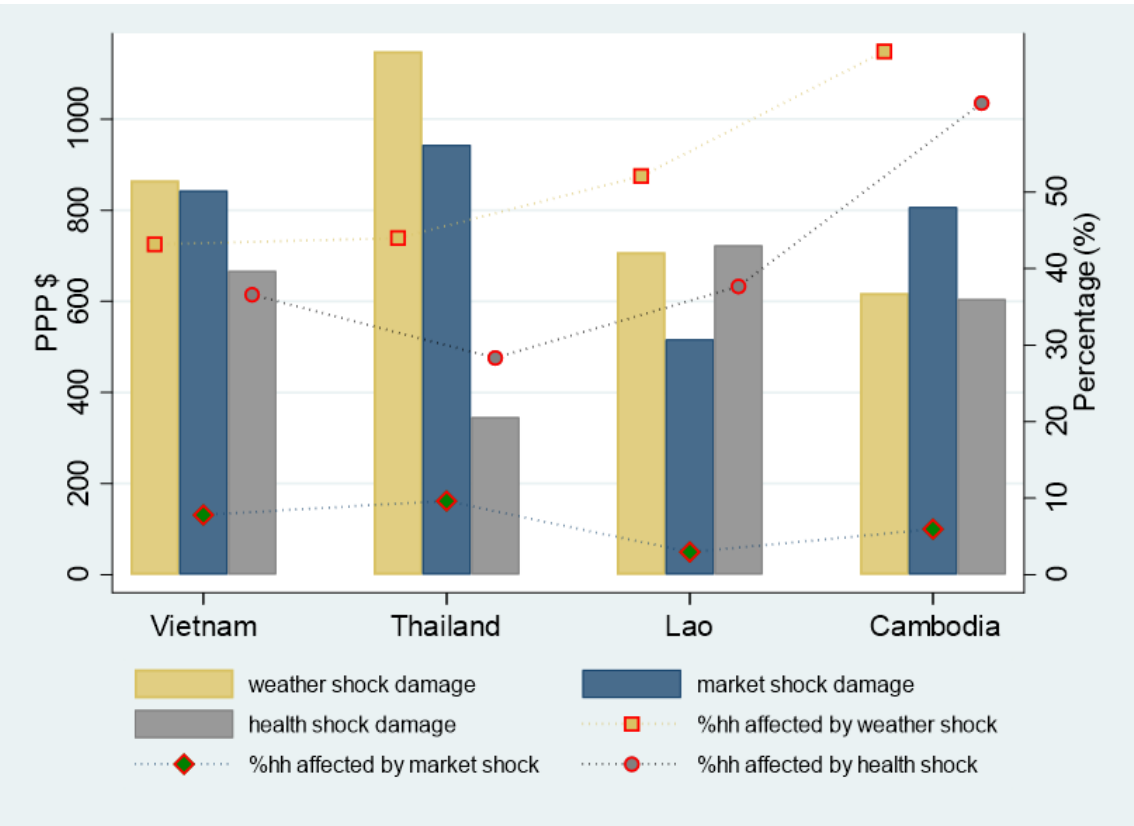

Figure 2. Percentage of affected households and average damages of shocks

3.3. Methodology

3.3.1 Impact of shocks on agricultural productivity

The first step of our empirical analysis is to estimate the impact of shocks and other household and village characteristics on agricultural productivity. This productivity is represented by two indicators: crop yields (total crop output value per hectare) and crop income per hectare. Crop yields are positive for all farmers, therefore, it is transformed into the logarithmic form in order to reduce potential outliers in value. Meanwhile, as some surveyed households report negative farm income, we use the absolute value of this indicator. We apply an Ordinary Least Squares (OLS) regression to estimate agricultural productivity and this model is specified as:

$$A_i = \alpha + \beta S_i + \delta H_i + \vartheta V_i + \epsilon_i \quad (1)$$

where A denotes either the natural logarithm of crop yields or crop income per hectare of household i. S_i represents shocks that household i faced in the last three years. H_i is the vector representing household characteristics. V_i is the vector capturing the village characteristics and ϵ is the error term. All monetary variables are measured in 2005 Purchasing Power Parity dollar (2005 PPP$). As our study is conducted in four different countries, we estimate equation (1) for each country separately.

Shocks are categorized into three main groups, namely weather shocks (e.g. floods, drought, and storms), health shocks (e.g. illness or death), and market shocks (e.g. increase in input price or decrease in output price). To prevent reporting and measurement errors, we drop shock events that are reported to have no impact and cause no losses. Household characteristics include age of household head, household size, share of male labor force (age above 15 and less than 61), share of literate members, land area, irrigated land area, share of rice-planted area, share of fruit-planted area, number of land plots, tractor value (in ln form) and total asset value per capita (in ln form). Village characteristics are represented by the availability of enterprises, distance to the nearest market, share of households having access to electricity, and province dummies. The detailed definition and dimension of these dependent and independent variables are described in Appendix A1. In addition, we apply the variance inflation test (VIF) to detect potential perfect multicollinearity, and the results of the test reject the null hypothesis (see Appendix A2).

3.3.2. Impact of agricultural productivity on natural resource extraction

In the second step, we identify the effects of agricultural productivity on natural resource extraction by estimating the following model:

$$E_i = \gamma + \rho A_i + \varphi S_i + \tau H_i + \theta V_i + \varepsilon_i \quad (2)$$

where E_i is total output value of extracted products (in ln form) of household i. A_i is households' crop yields (in ln form). S_i is the vector representing the incidence of various types of shocks that household i faced in the last three years. H_i is household characteristics. V_i is village characteristics and ε is the error term. The detailed definition and dimension of these dependent and independent variables are described in Appendix A1.

As crop yield is a dependent variable in Equation (1), it is likely endogenous in estimating natural resource extraction as in Equation (2). To deal with this, we follow the heteroscedastic-based instruments method proposed by Lewbel (2012). This method allows us to generate internal instruments. Internal instrumental variables (IVS) for A_i in estimating natural resource extraction in Equation (2) are constructed as: $[z_i' - E(z_i')]\hat{\xi}_i$. With ξ and *z* are the residuals and exogenous variables in Equation 1, respectively. IVS are uncorrelated with ε_i in Equation (2) as it is assumed that $Cov(z_i', \varepsilon_i) = Cov(z_i', \xi_i) = Cov(z_i', \varepsilon_i \xi_i) = 0$. Meanwhile, due to the existence of heteroscedasticity ($Cov(z_i', \xi_i^2) \neq 0$), IVS are correlated with A_i through ξ_i. In addition, as Lewbel (2012) suggests, we use an additional external instrument to improve efficiency of this approach by employing the average crop yield per household in the village.

To ensure the validity of our estimation, a number of post-estimation tests for underidentification, overidentification and weak instruments are conducted; the results of these tests confirm the validity of our model (see Tables 3 and 4). In addition, we also apply the VIF test to detect potential perfect multicollinearity and the results of the test reject the null hypothesis (see Appendix A3). In addition, as robustness checks, we examine the impact of crop income per hectare on natural resource extraction and these results are highly consistent with the estimation results of equation 2.

4. Results and Discussion

4.1. Impact of shocks on agricultural productivity

Table 3 shows the estimation of the effects of shocks on agricultural productivity. In particular, column 1 shows the impact of shocks on the natural logarithm of crop yields, meanwhile, the impact on crop income is presented in column 2. Models' summary statistics and diagnostics parameters are presented in the lower section of Table 1 with the p-value of the Wald chi^2 being statistically significant at the 1% level, confirming the validity of our estimation.

Our findings show that several factors are significantly associated with agricultural productivity such as weather shocks, land size, irrigation, farm mechanization, and household's education levels. The incidence of weather shocks significantly reduces crop yields and crop income. This makes sense as weather shocks directly cause crop losses and damages. In addition, weather shocks are shown as the most common and cause the most severe damages to households in our study sites (see Figure 2).

Table 3. Impact of shocks on agricultural productivity

	OLS models	
	Crop yields (in ln, PPP per ha)	**Crop income (PPP per ha)**
weather shock	-0.143***	-600.791***
	(0.026)	(121.335)
health shock	-0.013	-192.356
	(0.027)	(121.009)
market shock	0.065	119.729
	(0.048)	(258.289)
age head	0.002**	2.081
	(0.001)	(4.356)
share of literate members	0.241***	584.034**
	(0.061)	(269.835)
household size	0.011	23.561
	(0.007)	(35.612)
share of male laborers	0.020	175.538
	(0.064)	(329.405)
total asset value per capita (ln)	0.060***	121.666**
	(0.011)	(51.276)
tractor value (ln)	0.004***	-2.224
	(0.001)	(6.478)
land area	-0.139***	-368.734***
	(0.014)	(55.566)
land area squared	0.004***	10.898***
	(0.001)	(2.873)
irrigated land area	0.091***	306.251***
	(0.021)	(88.561)
no of land plots	-0.002	-140.734***
	(0.007)	(36.532)
share of rice-planted land	-0.310***	-2229.749***
	(0.040)	(237.719)
(village) distance to market	-0.001	-5.296
	(0.001)	(3.803)
(village) having enterprises	0.112***	274.168
	(0.038)	(209.797)
(village) electricity access	0.219***	641.579**
	(0.069)	(266.462)
Constant	7.217***	3424.135***
	(0.143)	(643.570)
province dummies	yes	yes
No of observations	4213	4213
R^2	0.346	0.131
Adjusted R^2	0.342	0.126
P-value	0.000	0.000

*Robust standard errors in parentheses; *** p<0.01, **p<0.05, * p<0.1*

In a related vein, a study in Cambodia by Mishra et al. (2018) also shows that weather shocks are a major cause of agricultural inefficiency. Households are less able to cope with extreme weather events as these shocks affect a large number of people in the region, causing severe damages to houses, croplands, and infrastructure, disrupting severely transportation and communication across regions (Nguyen et al., 2020; Kurosaki, 2015; De Silva and Kawasaki, 2018). In Table 4, we also disentangle the impact of shocks by countries. The incidence of weather shocks is negatively associated with crop yields and crop income in all countries, although the impacts are not statistically significant in Laos. The insignificant impact in Laos could be explained by the fact that the average damages and losses due to weather shocks in Laos are less severe than in Vietnam and Thailand (see Figure 2). This is also consistent with Eckstein et al. (2019), who show that Laos is generally less vulnerable to climate risks than Vietnam, Thailand, or Cambodia.

With regard to other household and village characteristics, Table 3 shows that land area is negatively and significantly correlated with farm productivity indicators, whereas the impact of the square of land area is positively significant. This is in line with Helfand and Levine (2004), who show a non-linear relationship between farm size and agricultural efficiency, with efficiency first falling and then rising with size. This is reasonable as small-scale farmers might be more efficient in using their scarce resources, and they could monitor their production activities more closely (Ebers et al., 2017; Fan and Kang, 2005). However, if land area is large enough, farmers could adopt machinery and modern technologies in the production process, therefore fostering their agricultural productivity. This is also consistent with our findings that the value of tractor, an indicator of farm mechanization is positively and significantly correlated with crop yields. Our findings also show that the impact of irrigated land area on crop yields and crop income is positive and significant. Meanwhile, the number of land plots, an indicator of land fragmentation, is negatively associated with crop income per hectare. This makes sense as land fragmentation may inhibit the adoption of machinery, and increase production and transportation costs. Our results also show that the share of rice-planted area is negatively correlated with both crop yields and crop income. This is in line with Mainuddin and Kirby

(2009). Their results on the Lower Mekong Basin (Vietnam, Lao, Thailand, Cambodia) show that the economic productivity of rice in this region is much lower than that of other crops such as maize, corn, and sugarcane. In addition, our findings show that households with older heads and higher education levels tend to have higher agricultural productivity. Isoto et al. (2017) also reveal that education and experience are among the major factors fostering the productivity of farmers. With regard to village characteristics, electricity access is found to have positive impacts on agricultural productivity. An explanation is that rural electrification facilitates the adoption of machinery and accelerates agricultural mechanization processes. In addition, our results show that distance to markets is negatively associated with agricultural productivity, whereas, having enterprise in the village has a positive effect on agricultural productivity. This is consistent with Ebers et al. (2017), who show that households living in remote areas appear to be less efficient in farming as they may face barriers in access to information, credit, inputs, and modern technologies.

Table 4. Impact of shocks on agricultural productivity by countries

	OLS models			
Panel A: Impact of shocks on crop yields (ln, PPP per ha)				
	Cambodia	**Laos**	**Thailand**	**Vietnam**
weather shock	-0.150*	-0.063	-0.170***	-0.069*
	(0.088)	(0.070)	(0.038)	(0.042)
health shock	0.018	0.113	-0.024	-0.016
	(0.081)	(0.074)	(0.045)	(0.041)
market shock	0.232	0.083	-0.016	0.121
	(0.183)	(0.225)	(0.070)	(0.075)
control variables	yes	yes	yes	yes
No of observations	503	507	1578	1625
R^2	0.159	0.165	0.109	0.232
Adjusted R^2	0.130	0.136	0.098	0.223
P-value	0.000	0.000	0.000	0.000
Panel B: Impact of shocks on crop income per hectare (PPP per ha)				
	Cambodia	**Laos**	**Thailand**	**Vietnam**
weather shock	-1040.087***	-85.379	-644.898***	-369.883*
	(338.341)	(93.812)	(202.843)	(218.420)
health shock	260.078	-18.251	-177.081	-221.389
	(337.115)	(160.613)	(186.349)	(228.821)
market shock	1199.679	188.538	-97.981	130.479
	(1347.807)	(465.677)	(296.207)	(467.335)
control variables	yes	yes	yes	yes
No of observations	503	507	1578	1625
R^2	0.197	0.089	0.101	0.108
Adjusted R^2	0.169	0.057	0.090	0.097
P-value	0.000	0.000	0.000	0.000

*Robust standard errors in parentheses; *** p<0.01, **p<0.05, * p<0.1*

4.2. Impact of agricultural productivity on natural resource extraction

Table 5 presents the estimation of total extraction output value. In particular, column 1 shows the impact of crop yields on total extraction output value, whereas the impact of crop income is shown in column 2. The models' summary statistics and diagnostics parameters, presented in the lower section of the table, show that all tests for overidentification, underidentification and weak instruments meet statistical requirements, confirming the validity and relevance of our models.

Table 5. Impact of agricultural productivity on natural resource extraction

	Heteroscedasticity-Based Instruments	
	Extraction output value (ln)	**Extraction output value (ln)**
crop yields (ln)	-0.938***	-
	(0.228)	-
crop income per hectare	-	-0.0001***
	-	(0.00003)
weather shock	1.262***	1.331***
	(0.237)	(0.234)
health shock	-0.316	-0.326
	(0.234)	(0.234)
market shock	1.059**	1.007**
	(0.447)	(0.445)
age head	-0.044***	-0.045***
	(0.009)	(0.009)
share of literate	-2.507***	-2.708***
	(0.497)	(0.494)
household size	0.139**	0.130**
	(0.061)	(0.062)
share of male labor force	1.889***	1.862***
	(0.585)	(0.582)
total asset value per capita (ln)	-0.788***	-0.817***
	(0.094)	(0.093)
tractor value (ln)	0.073***	0.067***
	(0.013)	(0.013)
land area	-0.090	-0.024
	(0.110)	(0.102)
land area squared	-0.004	-0.004
	(0.004)	(0.004)
irrigated land	-0.081	-0.151
	(0.161)	(0.160)
no of land plots	-0.001	-0.017
	(0.069)	(0.069)
share of rice-planted land	-1.252***	-1.252***
	(0.317)	(0.318)
(village) distance to market	0.023***	0.022***
	(0.007)	(0.007)
(village) having enterprises	-0.231	-0.268
	(0.366)	(0.364)
(village) electricity access	-1.034**	-1.184**
	(0.524)	(0.524)
constant	13.372***	6.903***
	(2.011)	(1.112)
province dummies	yes	yes
No of observations	4213	4213
R^2	0.279	0.282
Adjusted R^2	0.275	0.278
P-value	0.000	0.000
Underidentification	0.000	0.000
Overidentification	0.925	0.034
Weak identification	63.499	162.843

**** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses; the underidentification test is an LM test based on Kleibergen and Paap (2006) rk LM statistics with the null hypothesis that the model is underidentified. The overidentification test is based on the Hansen J test with the null hypothesis of all instruments being valid. For weak identification, Kleibergen-Paap rk Wald F statistics is reported.*

Our results show that both crop income per hectare and crop yields per hectare are significantly and negatively associated with total extraction output. In other words, this indicates that enhancing agricultural productivity will discourage farmers from natural resource extraction. This result is in line with Illukpitiya and Yanagida (2010) and Nguyen et al. (2018b) who show that natural resource extraction is a decreasing function of agricultural efficiency. Increasing agricultural productivity will make farming activities more profitable, therefore, positively affecting the opportunity cost of extraction activities. In addition, raising agricultural productivity make farmers wealthier, allowing them to substitute market goods for forest goods (Illukpitiya and Yanagida, 2010). Regarding the impact of shocks on natural resource extraction, weather shocks are significantly and negatively associated with the extraction output. Nguyen et al. (2020) and Takasaki et al. (2004) also show that extracting natural resources is a major coping strategy that households adopt to cope with extreme weather events. This makes sense as these shocks affect most households in a community, consequently, safety-net mechanisms that depend on the community (e.g., borrowing money, receiving remittance) may become less viable because relatives, friends, and neighbors all may also be negatively affected by the same shock.

With regard to other household and village characteristics, better-off households (those with a higher value of total asset per capita) and those with higher education levels appear to have a lower value of extraction output. This makes sense as poor households with lower education might have less access to remunerative response options, therefore, they rely more on natural resource-based coping strategies (Wunder et al., 2014). With regard to demographic characteristics, household size and share of male labor force are positively associated with natural resource extraction, whereas the impact of age of household head is negative. This is reasonable, as natural resource extraction activities are time-consuming and highly labor-intensive; therefore, households with more labor force, particularly, young labor force, are able to extract more natural resources. It is also argued that young households tend to rely more on natural resource extraction as they have not yet accumulated sufficient assets, land, and other physical capital to serve as a buffer (Wunder et al., 2014). With regard to village characteristics, distance to markets is positively correlated with natural resource extraction. Meanwhile, electricity access and the availability of enterprises in the village are negatively associated with natural resource extraction. This is reasonable, as the availability of alternative employment opportunities (e.g. non-farm jobs) increases the opportunity costs of extraction activities, consequently deterring households from extracting natural resources (Angelsen and Kaimowitz, 1999; Nguyen et al., 2015).

In Table 6, we show the estimations of total extraction output by countries. In particular, panel A shows the impact of crop yields on total extraction output, whereas the impact of crop income is shown in panel B. The estimations for Cambodia, Laos, Vietnam, and Thailand are shown in column 1, 2, 3, and 4, respectively. Our results show that enhancing crop productivity could significantly reduce natural resource extraction in all countries. With respect to shocks, our results show that the incidence of weather shocks is positively associated with the value of extraction output in all surveyed countries, although the impact of weather shocks in Thailand is statistically insignificant. Market shocks are shown to significantly increase natural resource extraction in Thailand. This is reasonable as the economy in Thailand is more developed, households get more involved in the market, and they are more likely affected by market shocks. This is consistent with our results in Figure 2, showing that Thai farmers are more likely affected by market shocks. Furthermore, the damages due to these shocks are more severe in Thailand than in the other surveyed countries. Our results also show that health shocks have negative impacts on natural resource extraction in Laos. This is consistent with the notion that losses of labor availability due to health shocks negatively affect the use of labor-intensive coping strategies such as natural resource extraction (Angelsen et al., 2014; Wunder et al., 2014). Figure 2 also shows that, on average, health shocks cause the highest damages to households in Laos. This is in line with Wagstaff (2014) who shows that health shocks are more common and more costly than most other types of shocks in Laos.

Table 6. Impact of agricultural productivity on natural resource extraction by countries

	Heteroscedasticity-Based Instruments			
	Extraction output value (ln)			
	Cambodia	**Laos**	**Thailand**	**Vietnam**
Panel A: The impact of crop yields				
crop yields (ln)	-0.867*	0.028	-0.719*	-0.682**
	(0.493)	(0.509)	(0.422)	(0.344)
weather shock	1.935***	1.397***	0.233	1.428***
	(0.732)	(0.519)	(0.414)	(0.363)
health shock	-0.139	-0.897*	-0.636	-0.099
	(0.598)	(0.499)	(0.429)	(0.358)
market shock	0.853	-0.970	2.171***	0.861
	(0.990)	(1.802)	(0.668)	(0.686)
control variables	yes	yes	yes	yes
No of observations	503	507	1578	1625
R^2	0.137	0.177	0.090	0.282
P-value	0.000	0.000	0.000	0.000
Underidentification	0.000	0.000	0.000	0.000
Overidentification	0.424	0.347	0.553	0.105
Weak identification	29.093	14.944	46.879	24.048
Panel B: The impact of crop income				
	Cambodia	**Laos**	**Thailand**	**Vietnam**
crop income per hectare	-0.0003***	-0.0004***	-0.0001**	-0.0001**
	(0.00007)	(0.00008)	(0.00005)	(0.0004)
weather shock	1.826**	1.534***	0.271	1.485***
	(0.724)	(0.512)	(0.405)	(0.359)
health shock	0.115	-1.014**	-0.577	-0.078
	(0.597)	(0.517)	(0.427)	(0.356)
market shock	1.122	-1.961	2.079***	0.785
	(0.954)	(1.866)	(0.671)	(0.687)
control variables	yes	yes	yes	yes
No of observations	503	507	1578	1625
R2	0.150	0.182	0.094	0.282
P-value	0.000	0.000	0.000	0.000
Underidentification	0.033	0.024	0.000	0.000
Overidentification	0.557	0.194	0.343	0.077
Weak identification	161.088	703.182	109.624	38.009

**** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses; the underidentification test is an LM test based on Kleibergen and Paap (2006) rk LM statistics with the null hypothesis that the model is underidentified. The overidentification test is based on the Hansen J test with the null hypothesis of all instruments being valid. For weak identification, Kleibergen-Paap rk Wald F statistics is reported.*

5. Conclusion

Natural resource extraction is among the most important livelihood strategies for rural households in developing countries. However, in Southeast Asia and many parts of the world, environmental resources are degrading at an alarming rate. Therefore, understanding the underlying factors of environmental resource dependence can help to reduce and prevent the degradation of environmental resources. Given an ambiguous relationship between shocks, agricultural productivity, and natural resource extraction, our study aims to investigate these relationships by using a large dataset of above 4,000 households collected in four Southeast Asian countries, including Cambodia, Laos, Thailand, and Vietnam. In particular, we first apply OLS models to investigate the impact of shocks, including health shocks, weather shocks, and market shocks, on agricultural productivity. Then, a heteroscedasticity-based instruments approach is applied to study the impact of agricultural productivity on natural resource extraction.

With regard to the impact of shocks on crop yields, our results show that weather shocks cause a significant and negative impact on agricultural productivity. For household and village characteristics, our results show a non-linear relationship between land area and agricultural productivity, with productivity first falling and then rising with land area. Land fragmentation is negatively associated with agricultural productivity. Meanwhile, the impact of irrigated land area is positive and significant. Our findings also show that households with older heads and higher education levels tend to have higher agricultural productivity. With regard to village characteristics, electricity access and the availability of enterprises have positive effects on agricultural productivity.

Regarding the estimation for natural resource extraction, our results show that natural resource extraction is negatively associated with agricultural productivity. For the impact of shocks, weather shocks and market shocks are positively correlated with the value of extraction output. In particular, weather shocks trigger households to extract more natural resources in all countries. Market shocks are positively and significantly correlated with natural resource extraction in Thailand. Meanwhile, health shocks are negatively and significantly associated with the extraction in Laos. In terms of household characteristics, households with higher education levels appear to extract fewer natural resources. Household size and share of male labor force are positively associated with natural resource extraction, whereas the impact of age of household head is negative. With regard to village characteristics, living in a village that is nearer to markets, has enterprises and electricity access discourages households to extract natural resources.

Our results also provide several important implications for the government and policymakers. First, enhancing agricultural productivity should be prioritized as it discourages households to extract natural resources. Second, the governments have to provide more assistance and support to farmers in mitigating the severe effect of weather shocks as these extreme events undermine not only agricultural productivity, but they also push households into extraction activities. The severe impact of market shocks on natural resource extraction also needs to be taken into account in Thailand. In addition, we suggest promoting rural education as this would enable rural farmers to improve agricultural productivity and extract fewer natural resources. In addition, accelerating rural electrification and supporting the development of local enterprises should also be implemented.

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Appendices

A1. Name and definition of variables in regression models

Name	Unit	Definition
crop yields (ln)	PPP$ 2005	Value of all crops that households harvested in the last 12 months
weather shock	yes=1,no=0	Households suffer from at least one weather shock (flood, drought, storm, heavy rainfall, cold period) in the last 3 years
health shock	yes=1,no=0	Households suffer from at least one health shocks (death, illness) in the last 3 years
market shock	yes=1,no=0	Households suffer from at least one market shocks (changes of output and input price in the market) in the last 3 years
age head	years	Age of household head
share of literate members	proportion	Share of literate members per household
household size	members	Number of household members
share of male laborers	proportion	Share of male members (age >14&<60) per household size
total asset value per capita (ln)	PPP$ 2005	Total value of assets that household owns
tractor value (ln)	PPP$ 2005	Total value of tractors that household owns
land area	hectare	Total land area that household owns or uses
irrigated land area	hectare	Total irrigated land area
no of land plots	numbers	Number of land plots
share of rice-planted land	proportion	Share of crop land for planting rice
(village) electricity access	proportion	Share of households have access to electricity
(village) distance to market	kilometers	Distance from village center to the nearest market
(village) having enterprises	yes=1,no=0	Village have at least one enterprise with more than 7 employees

A2. Collinearity test of estimations for crop yields

	Whole sample	Laos	Cambodia	Thailand	Vietnam
Variables	VIF	VIF	VIF	VIF	VIF
weather shock	1.09	1.07	1.08	1.14	1.1
health shock	1.06	1.05	1.05	1.06	1.05
market shock	1.04	1.03	1.11	1.06	1.03
age head	1.2	1.1	1.19	1.08	1.19
share of literate	1.54	1.44	1.26	1.09	1.27
household size	1.33	1.27	1.19	1.15	1.31
share of male laborer	1.04	1.07	1.06	1.04	1.08
total asset value per capita (ln)	1.65	2.62	1.78	1.33	1.39
tractor value (ln)	1.48	2.39	1.68	1.28	1.38
land area	3.08	8.04	6.16	6.21	4.9
land area squared	4.21	7.23	20.54	4.94	3.82
irrigated land area	2.55	1.08	11.46	1.08	1.73
no of land plots	1.52	1.28	1.39	1.54	1.27
share of rice-planted land	1.67	1.17	1.7	1.43	1.63
(village) electricity access	2.86	1.4	1.24	1.11	1.11
(village) distance to market	1.5	1.15	1.08	1.13	1.34
(village) having enterprises	1.1	1.14	1.11	1.07	1.13
Stung Treng (Cambodia)	2.6				
Svannakhet (Laos)	3.87				
Buriram (Thailand)	2.6				
Ubon Ratchathani (Thailand)	2.72			1.53	
Nakkhon Phanom (Thailand)	1.8			1.47	
Daklak (Vietnam)	2.23				1.96
Ha Tinh (Vietnam)	1.93				2.24
Mean VIF	1.96	2.04	3.21	1.66	1.66

A3. Collinearity test of estimations for extraction output value

	Whole sample	Laos	Cambodia	Thailand	Vietnam
Variables	VIF	VIF	VIF	VIF	VIF
crop yield	1.52	1.2	1.19	1.12	1.29
weather shock	1.12	1.08	1.07	1.16	1.08
health shock	1.08	1.04	1.03	1.06	1.05
market shock	1.04	1.02	1.12	1.06	1.03
age head	1.24	1.1	1.16	1.18	1.2
share of literate	1.58	1.48	1.3	1.1	1.27
household size	1.31	1.27	1.18	1.13	1.3
share of male laborer	1.13	1.05	1.08	1.2	1.19
total asset value per capita (ln)	1.64	2.57	1.77	1.28	1.43
tractor value (ln)	1.49	2.37	1.67	1.26	1.39
land area	4.8	9.38	6.8	5.26	5.39
land area squared	3.39	7.94	5.41	3.64	3.33
irrigated land area	1.26	1.08	1.13	1.11	1.88
no of land plots	1.65	1.32	1.48	1.8	1.31
share of rice-planted land	1.41	1.04	1.09	1.15	1.52
(village) electricity access	1.5	1.14	1.08	1.13	1.37
(village) distance to market	1.1	1.13	1.11	1.07	1.12
(village) having enterprises	2.87	1.41	1.24	1.11	1.12
Stung Treng (Cambodia)	3.02				
Svannakhet (Laos)	4.02				
Buriram (Thailand)	2.55				
Ubon Ratchathani (Thailand)	2.73			1.55	
Nakkhon Phanom (Thailand)	1.79			1.49	
Daklak (Vietnam)	2.15				2
Ha Tinh (Vietnam)	2.2				1.97
Mean VIF	1.98	2.15	1.77	1.54	1.66

A4. Impact of shocks on crop yields by countries

	OLS models			
	Cambodia	**Laos**	**Thailand**	**Vietnam**
weather shock	-0.150*	-0.063	-0.170***	-0.069*
	(0.088)	(0.070)	(0.038)	(0.042)
health shock	0.018	0.113	-0.024	-0.016
	(0.081)	(0.074)	(0.045)	(0.041)
market shock	0.232	0.083	-0.016	0.121
	(0.183)	(0.225)	(0.070)	(0.075)
age head	0.005*	0.006**	-0.002	0.002
	(0.003)	(0.003)	(0.002)	(0.002)
share of literate	0.106	0.272**	0.285**	0.265**
	(0.144)	(0.131)	(0.120)	(0.110)
household size	-0.001	-0.013	0.017	0.022*
	(0.023)	(0.017)	(0.012)	(0.012)
share of male laborer	-0.322	0.130	0.101	-0.020
	(0.274)	(0.249)	(0.095)	(0.102)
total asset value per capita (ln)	-0.005	-0.021	0.029*	0.116***
	(0.029)	(0.043)	(0.015)	(0.020)
tractor value (ln)	0.005	0.021***	0.002	0.004
	(0.005)	(0.007)	(0.002)	(0.003)
land area	-0.148***	-0.404***	-0.076***	-0.347***
	(0.039)	(0.060)	(0.018)	(0.054)
land area squared	0.004**	0.028***	0.002**	0.022***
	(0.002)	(0.006)	(0.001)	(0.005)
irrigated land	0.014	-0.005	0.016	0.267***
	(0.048)	(0.052)	(0.022)	(0.040)
no of land plots	-0.004	0.103	0.029*	-0.015*
	(0.060)	(0.099)	(0.015)	(0.008)
share of rice-planted land	-0.133	-0.010	-0.465***	-0.505***
	(0.088)	(0.083)	(0.096)	(0.065)
(village) distance to market	0.000	0.001	-0.001	-0.018***
	(0.002)	(0.002)	(0.002)	(0.006)
(village) having enterprises	0.025	0.125	-0.012	0.135**
	(0.425)	(0.152)	(0.058)	(0.053)
(village) electricity access	0.489***	0.222**	0.304	0.065
	(0.159)	(0.097)	(0.198)	(0.152)
constant	7.375***	6.573***	7.414***	7.307***
	(0.311)	(0.367)	(0.295)	(0.288)
province dummies	-	-	yes	yes
No of observations	503	507	1578	1625
R^2	0.159	0.165	0.109	0.232
Adjusted R^2	0.130	0.136	0.098	0.223
P-value	0.00	0.00	0.00	0.00

*Robust standard errors in parentheses; *** p<0.01, **p<0.05, * p<0.1*

A5. Impact of shocks on crop income per ha by countries

	OLS models			
	Cambodia	**Laos**	**Thailand**	**Vietnam**
weather shock	-1040.087***	-85.379	-644.898***	-369.883*
	(338.341)	(93.812)	(202.843)	(218.420)
health shock	260.078	-18.251	-177.081	-221.389
	(337.115)	(160.613)	(186.349)	(228.821)
market shock	1199.679	188.538	-97.981	130.479
	(1347.807)	(465.677)	(296.207)	(467.335)
age head	22.002	8.618**	-5.035	-2.491
	(14.094)	(4.344)	(7.051)	(9.549)
share of literate	144.557	464.547	822.250**	392.816
	(774.905)	(283.232)	(373.754)	(604.054)
household size	-66.221	27.532	31.941	42.781
	(135.765)	(38.250)	(55.269)	(78.698)
share of male laborer	-403.406	508.108	222.717	55.495
	(1428.981)	(585.341)	(479.354)	(591.957)
total asset value per capita (ln)	-14.122	26.172	-69.615	415.628***
	(92.587)	(75.964)	(75.274)	(117.736)
tractor value (ln)	-8.222	-7.177	-3.622	8.237
	(14.757)	(16.197)	(8.222)	(13.655)
land area	-260.126**	-530.273***	-277.383***	-1171.884***
	(107.126)	(160.512)	(85.196)	(219.507)
land area squared	6.504*	41.244***	5.923**	84.315***
	(3.704)	(15.052)	(2.990)	(22.450)
irrigated land	187.330	-35.030	37.156	786.077***
	(225.527)	(127.119)	(69.389)	(147.754)
no of land plots	-625.306***	-86.340	-3.093	-140.794***
	(240.312)	(316.755)	(59.692)	(46.017)
share of rice-planted land	-1381.064***	-403.110*	-2995.755***	-3332.212***
	(338.587)	(219.279)	(633.185)	(450.995)
(village) distance to market	-1.709	-1.192	-3.048	-36.923*
	(5.470)	(2.304)	(12.427)	(19.214)
(village) having enterprises	-292.340	568.805	-113.872	255.717
	(1898.693)	(670.881)	(183.781)	(347.311)
(village) electricity access	1949.949***	-24.750	425.854	471.617
	(684.208)	(159.470)	(640.560)	(652.070)
constant	4266.229***	1063.787*	4755.564***	3488.514**
	(1499.108)	(620.697)	(1318.330)	(1506.787)
province dummies	-	-	yes	yes
No of observations	503	507	1578	1625
R^2	0.197	0.089	0.101	0.108
Adjusted R^2	0.169	0.057	0.090	0.097
P-value	0.00	0.00	0.00	0.00

*Robust standard errors in parentheses; *** p<0.01, **p<0.05, * p<0.1*

A6. Impact of crop yields on natural resource extraction by countries

	Heteroscedasticity-based Instruments			
	Extraction output value (ln)			
	Cambodia	**Laos**	**Thailand**	**Vietnam**
crop yields (ln)	-0.867*	0.028	-0.719*	-0.682**
	(0.493)	(0.509)	(0.422)	(0.344)
weather shock	1.935***	1.397***	0.233	1.428***
	(0.732)	(0.519)	(0.414)	(0.363)
health shock	-0.139	-0.897*	-0.636	-0.099
	(0.598)	(0.499)	(0.429)	(0.358)
market shock	0.853	-0.970	2.171***	0.861
	(0.990)	(1.802)	(0.668)	(0.686)
age head	0.026	-0.051***	-0.071***	-0.045***
	(0.023)	(0.018)	(0.017)	(0.014)
share of literate	-3.528***	-2.861***	-0.270	-3.438***
	(0.991)	(0.950)	(1.085)	(0.872)
household size	0.100	0.192*	0.094	0.070
	(0.160)	(0.116)	(0.120)	(0.109)
share of male laborer	3.474*	-2.692	2.294**	1.693*
	(1.804)	(1.914)	(0.959)	(0.871)
total asset value per capita (ln)	-0.048	-0.455*	-0.935***	-1.136***
	(0.242)	(0.253)	(0.159)	(0.165)
tractor value (ln)	0.050	0.112**	0.082***	0.017
	(0.040)	(0.047)	(0.020)	(0.022)
land area	-0.261	0.235	-0.197	0.440
	(0.276)	(0.499)	(0.160)	(0.433)
land area squared	-0.002	-0.026	0.003	-0.029
	(0.010)	(0.045)	(0.004)	(0.056)
irrigated land	0.783***	-1.633**	0.541**	-0.718**
	(0.191)	(0.666)	(0.251)	(0.290)
no of land plots	0.839**	0.878*	-0.143	0.071
	(0.418)	(0.508)	(0.144)	(0.087)
share of rice-planted land	-0.208	-1.204**	-0.016	-1.438***
	(0.680)	(0.558)	(0.685)	(0.539)
(village) distance to market	0.023**	0.007	-0.000	0.107***
	(0.009)	(0.009)	(0.025)	(0.037)
(village) having enterprises	-1.986	-1.611	0.847	-0.111
	(3.716)	(1.326)	(0.646)	(0.472)
(village) electricity access	-2.459**	-1.735***	0.377	1.346
	(1.083)	(0.649)	(2.624)	(1.585)
constant	6.853	8.911**	10.605**	10.572***
	(4.298)	(4.139)	(4.539)	(3.378)
province dummies	-	-	yes	yes
No of observations	503	507	1578	1625
R^2	0.137	0.177	0.090	0.282
P-value	0.000	0.000	0.000	0.000
Underidentification	0.000	0.000	0.000	0.000
Overidentification	0.424	0.347	0.553	0.105
Weak identification	29.093	14.944	46.879	24.048

**** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses; the underidentification test is an LM test based on Kleibergen and Paap (2006) rk LM statistics with the null hypothesis that the model is underidentified. The overidentification test is based on the Hansen J test with the null hypothesis that all instruments are valid. For weak identification, Kleibergen-Paap rk Wald F statistics is reported.*

A7. Impact of crop income on natural resource extraction by countries

	Heteroscedasticity-based Instruments			
	Extraction output value (ln)			
	Cambodia	**Laos**	**Thailand**	**Vietnam**
crop income per ha	-0.0003***	-0.0004***	-0.0001**	-0.0001**
	(0.00007)	(0.00008)	(0.00005)	(0.0004)
weather shock	1.826**	1.534***	0.271	1.485***
	(0.724)	(0.512)	(0.405)	(0.359)
health shock	0.115	-1.014**	-0.577	-0.078
	(0.597)	(0.517)	(0.427)	(0.356)
market shock	1.122	-1.961	2.079***	0.785
	(0.954)	(1.866)	(0.671)	(0.687)
age head	0.027	-0.036**	-0.071***	-0.045***
	(0.022)	(0.018)	(0.017)	(0.014)
share of literate	-3.767***	-2.750***	-0.386	-3.589***
	(1.005)	(0.961)	(1.082)	(0.863)
household size	0.187	0.163	0.089	0.062
	(0.154)	(0.112)	(0.120)	(0.109)
share of male laborer	3.607**	-2.781	2.105**	1.760**
	(1.756)	(1.900)	(0.957)	(0.865)
total asset value per capita (ln)	-0.052	-0.590**	-0.966***	-1.201***
	(0.243)	(0.250)	(0.159)	(0.159)
tractor value (ln)	0.043	0.156***	0.078***	0.014
	(0.040)	(0.045)	(0.020)	(0.021)
land area	-0.362	-0.298	-0.114	0.637
	(0.266)	(0.465)	(0.159)	(0.399)
land area squared	0.005	0.001	0.000	-0.058
	(0.010)	(0.043)	(0.004)	(0.049)
irrigated land	0.768***	-1.234**	0.495*	-0.779***
	(0.194)	(0.614)	(0.254)	(0.273)
no of land plots	0.809*	1.378***	-0.164	0.062
	(0.426)	(0.480)	(0.144)	(0.086)
share of rice-planted land	-0.495	-1.439***	0.121	-1.326**
	(0.671)	(0.554)	(0.677)	(0.545)
(village) distance to market	0.022**	0.012	-0.001	0.113***
	(0.009)	(0.009)	(0.025)	(0.036)
(village) having enterprises	-2.858	-0.648	0.866	-0.111
	(3.763)	(1.274)	(0.648)	(0.466)
(village) electricity access	-2.106*	-1.120*	0.513	1.392
	(1.129)	(0.628)	(2.607)	(1.587)
constant	0.960	9.025***	5.408*	5.778**
	(2.291)	(2.225)	(3.258)	(2.397)
province dummies	-	-	yes	yes
No of observations	503	507	1578	1625
R^2	0.150	0.182	0.094	0.282
P-value	0.150	0.182	0.094	0.282
Underidentification	0.033	0.024	0.000	0.000
Overidentification	0.557	0.194	0.343	0.077
Weak identification	161.088	703.182	109.624	38.009

**** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses; the underidentification test is an LM test based on Kleibergen and Paap (2006) rk LM statistics with the null hypothesis that the model is underidentified. The overidentification test is based on the Hansen J test with the null hypothesis that all instruments are valid. For weak identification, Kleibergen-Paap rk Wald F statistics is reported.*