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The dynamics of Vietnam agriculture under changing conditions

A thesis

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The dynamics of Vietnam agriculture under changing conditions

Abstract

Although Vietnam has undergone fundamental transformation since the economic reforms in the late 1980s, agriculture continues to play a pivotal role in the economy. Given the rising food demand and declining availability of farmland areas, improvements in rice technology are vital for Vietnam to maintain food security and export status. Despite the rising application of high-yielding varieties, rice productivity growth slowed down. The sustainable development of Vietnam agriculture is facing additional challenges due to changing climate which is expected to affect several aspects of agriculture. To date, there has been little insight into how Vietnam agriculture is likely to be impacted by these drivers. This thesis is among the first studies which provided robust estimates of the impacts of technology change and climate change on the Vietnam agrarian economy.

Utilizing data from the Vietnam Access to Resources Household Surveys (VARHS) 2006 -2016, this thesis examined the major ongoing changes in Vietnam agriculture and likely impacts of these changes. Three specific relationships were examined: (1) The relationship between hybrid rice seeds and productivity; (2) the relationship between climate change and agricultural productivity; and (3) the relationship between changing climate and land use choice as an adaptation strategy and its likely impact on long-term food security.

The literature on hybrid rice has reported superior productivity of hybrid rice seeds over inbred varieties. This is not supported by our panel stochastic frontier estimates pertaining to productivity impact assessment for Vietnam. Estimates of a large managerial gap indicate a handsome benefit from efforts to increase productivity. Vietnam is expected to be among the countries hardest-hit by climate change. However the panel Ricardian model suggests marginal impacts, even in the long run when the projected changes are more severe.

Changing crops is an adaptation to climate change. The empirical findings from the Fractional Multinomial Logit model indicate the sensitivity of the Vietnam land use system to climate. Seasonal climates exert heterogeneous impacts on land use shares for different crops. The projected climate changes are expected to induce large shifts from cereals to annual industrial crops in the two rice bowls of the country.

This thesis made several contributions to impact assessments and suggested policy implications. First, the productivity impact assessment in Chapter 3 provides a simple way to control for selectivity bias in a panel stochastic frontier framework while allowing for direct comparisons of the base productivity, factor productivity, and technical efficiency. Second, the analyses of climate impacts and crop choice in Chapter 4 and Chapter 5 provide a simple way to relax the assumption of a constant effect of market feedbacks in climate change assessments and this avoids biased climate estimates. Finally, this thesis provides valuable policy implications regarding the development of rice technology and climate change adaptation in a developing country where agriculture supports income and employment for a large portion of the population.

Notes on publications

Several publications and working papers have been produced from this thesis. The list of the papers is as follows:

Working paper:

Chapter 2: An agro-economic history of the Vietnam rice sector

Published papers:

Chapter 3 has been published online in *Journal of Agricultural Economics*:

Nguyen, C. T., Scrimgeour, F. (2021). Productivity impacts of hybrid rice seeds in Vietnam. *Journal of Agricultural Economics*. doi:https://doi.org/10.1111/1477-9552.12458.

Chapter 4 has been published online in *Agricultural Economics:*

Nguyen, C. T., Scrimgeour, F. (2021). Measuring the impact of climate change on agriculture in Vietnam: A panel Ricardian analysis. *Agricultural Economics*. doi:https://doi.org/10.1111/agec.12677.

Chapter 5 is under review:

Trinh, N.C., Scrimgeour, F. (2021). Farm-level adaptations to climate change in Vietnam: Investigating the uptake of crop substitution.

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This thesis is dedicated to my beloved mother who passed away before I came to New Zealand. She has been my strength to fight with the toughness necessary to attain what we have desired.

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List of abbreviations

DIVA-GIS	Data-Interpolating Variational Analysis - Geographic information system
FAO	Food and Agriculture Organization
FIML	Full information maximum likelihood
GDP	Gross Domestic Product
GSO	General Statistical Office
ha	Hectare
HYV	High-yielding varieties
Kg	Kilogram
m^2	Square meter
MONRE	Ministry of Natural Resources and Environment
N	Number of observations
ºC	Degree Celsius
OECD	The Organisation for Economic Co-operation and Development
PSM	Propensity Score Matching
QMLE	Quasi-maximum likelihood estimator
R^2	R squared measuring the overall fitness of a regression
Std. Dev	Standard deviation
Std.err	Standard error
TE	Technical efficiency level
TFE	True Fixed Effects
TFP	Total factor productivity
TRE	True Random Effects
USD	United States dollar
VARHS	Vietnam Access to Resources Household Survey
VND	Vietnamese dong (Vietnamese currency)

Chapter 1. Introduction to the thesis

1.1. The Vietnam agricultural context

The on-going success of Vietnam agriculture, and the rice sector, has been attributed to the fast and steady economic performance of Vietnam (McCaig & Pavcnik, 2013; McCaig *et al.*, 2009). In the early 1980s, Vietnam was one of the five poorest countries (Glewwe, 2004) with barely any prospect for development. The series of reforms initiated in 1986 freed agriculture from the existing constraints on farmers and firms autonomy. With a large proportion of agricultural population, improvements in agricultural productivity and rural household incomes played a pivotal role in economic growth and equity. Rural household income rose by 11% per annum in the period 1993 – 1998 (Brandt & Benjamin, 2002), and by 7% per annum for the period 2002 - 2014 (Benjamin *et al.*, 2017). The main reasons for the increase in household incomes were increased earnings of agricultural laborers (Benjamin *et al.*, 2017; Ravallion, 2008) and off-farm job opportunities (Benjamin *et al.*, 2017).

The literature on the Vietnam agricultural transformation has focused on the economic reforms in the late 1980s (Jerez, 2018; Glewwe, 2004; Goletti, 2000; Pingali & Xuan, 1992) which motivated farmers to work harder and smarter. In addition, improved productivity and agricultural income of Vietnamese farmers has been attributed to the rising application of advanced technologies in the rice sector. Nghiem and Coelli (2002) estimated an average of 3.5% of TFP growth of the Vietnam rice sector between 1976 and 1997 of which technical change made up the most part. Che *et al.* (2006) showed that agricultural innovation played an important role (up to 80%) in accelerating agricultural growth in Vietnam during the reforms.

Since the easy part of productivity gains through improved varieties and higher input intensity have been achieved, hybrid rice seeds have been regarded as the most important technology coping with the food security concern for Vietnam (Ut & Kajisa, 2006). Significant funds have been allocated to imported hybrid rice seeds. Despite this, rice productivity growth slowed down, from 1.8 percent per annum between 2006 and 2010 to 0.8 percent between 2010 and 2016. The slowdown in rice productivity raised concern over Vietnam rice technology development in the post-Green Revolution period. Unfortunately, no effort has been devoted to understanding how the post-Green Revolution is proceeding in the agrarian economy of Vietnam. There is also an open debate among development scholars over future prospects for agricultural growth. Ruttan (2002) expressed concern over prospects to sustain world agricultural growth as agricultural technology has begun to experience diminishing returns while Evenson and Gollin (2003), and Renkow and Byerlee (2010) documented no evidence of such slowdown in returns to improved crop varieties. Therefore, productivity impacts of hybrid rice merits thorough analysis given the pivotal role of rice in the Vietnam economy and Vietnam's status in the global rice market.

Future development of Vietnam agriculture is uncertain due to emerging challenges. Vietnam is expected to be among the countries hardest-hit by future climate change (Dasgupta *et al.*, 2009). A report by the Ministry of Natural Resources and Environment (MONRE, 2009) indicates non-uniform changes in climate patterns. Temperature is predicted to increase faster in autumn and winter. While the Northern region of the country will experience a shortage of rainfall in spring, the Southern region will suffer from lower precipitation for winter and spring. The small-scale nature of Vietnam agriculture with low adaptation capacity makes it more vulnerable to changing climate. Despite the growing evidence of such climate change, there has been little expertise on how Vietnam agriculture is likely to be affected by changing climate. Climate impact assessments are, therefore, of special interest to policy-makers as an inference to propose adaptation strategies.

1.2. Research objectives and research questions

This thesis is dedicated to exploring the dynamics of Vietnam agriculture in periods of changing policies, technology, and environmental conditions. Albeit with limited evidence, hybrid rice has been regarded as the driving force of improved agricultural productivity. Additionally, Vietnam is considered to be among the countries hardest-hit by future climate change. The likely consequences of changing climate can be declines in agricultural productivity and incomes, agricultural land losses, and changes in land use patterns which may affect food security. Climate change impact assessments are, therefore, crucial for adaptation policy. The primary objective of this thesis is to explore the major changing production conditions and their likely impacts on Vietnam agriculture. To meet the research objective, four interconnected studies were conducted to better understand the dynamics of Vietnam agriculture and the likely outcomes.

The first paper presented in chapter 2 provides an overview of the transformation of Vietnam agriculture, with a focus on the rice sector, in the latter half of the twentieth century. It provides a detailed picture of the dynamics of agriculture in changing environments: (1) technology change; (2) Input and output market reforms; (3) and agricultural support policy change. The study addresses the following research question: What were the factors driving the discrepancies in agricultural performance across regions? The paper applies the historical approach to explaining the dynamics of Vietnam agriculture. Data and supporting evidence come from numerous reports and journal articles that the author is able to access. The analysis shows that the fast transformation of Vietnam agriculture was the outcome of policy changes and technological advancements. In contrast to most previous thoughts on the growing income gap in favor of the rural South, this paper demonstrates that farmers in the Red River delta successfully managed to enjoy higher income growth despite limited farming areas. The bottleneck for future transformation of Vietnam agriculture is excessive land fragmentation.

The second analysis investigates the productivity impacts of hybrid rice seeds in Vietnam. The analysis seeks to answer the second research question: Does the adoption of hybrid rice seeds help improve rice productivity? Panel stochastic frontier models with correction for selectivity bias were estimated. The research findings from the seed selection model confirm the importance of input availability and market conditions in explaining adoption of hybrid rice. The panel stochastic frontier results indicate a lower base productivity of hybrid rice in the period studied. The analysis also indicates a stagnancy of agricultural technology as the results show an inward neutral technology change in the Vietnam rice sector between 2006 and 2016. However, a large managerial gap of 39% indicates a handsome benefit from efforts to increase productivity in Vietnam.

The third study endeavours to quantify the economic impacts of climate change on Vietnam agriculture. This paper addresses the following research question: What are the long-term impacts of climate change on Vietnam agriculture? The Ricardian approach to evaluating economic impact of climate change is applied to a ten-year panel of crop production using the two-stage Hsiao method. In contrast to previous panel Ricardian models assuming uniform effect of market shocks on households, we allow market shocks to have differentiated effects on different regions with different crop portfolios. The Ricardian model is then used to simulate how non-marginal changes in future climate will affect Vietnam. The climate simulation indicates marginal losses due to the projected climate changes on Vietnam agriculture, with net losses ranging from 0.02% to 2.6% across regions. While regions with cool climate such as the Central Highlands and the Northwest are likely to experience losses, the Red River delta is hardly affected at all. However, changing climate exerts heterogeneous seasonal and regional effects. Irrigation is a positive adaptation response that can mitigate negative impacts of climate change.

While the third study implicitly assumes full adaptation in terms of crop substitution, the fourth analysis in Chapter 5 is dedicated to investigating the uptake of crop substitution as an adaptation strategy to changing climate. The paper aims at addressing the following research questions: Have Vietnamese farmers adapted to the current climate by means of crop substitution? If yes, how will the projected climate change be likely to affect land use patterns in the future? A Fractional Multinomial Logit model is applied to a ten-year panel of household data to capture the competition across land use alternatives. We allow price feedbacks to have variable effects on different land use alternatives while the model relaxes the assumption on the additive separability of temperature and precipitation. Empirical findings suggest that Vietnamese farmers have adapted to the changing climate in terms of crop selection and this adaptation depends on household and farmland characteristics. Increases in winter and summer temperatures shift the farmland towards cereals. Farms in wet locations with colder winters and cooler summers are likely to choose cash crops. Farmers choose annual industrial crops in locations with warmer springs and autumns. Farms in wetter locations with warmer winters and cooler summers tend to choose fruit trees. The production of permanent industrial crops requires stable temperatures. These crops are preferred by farms in locations with warmer winters and cooler summers. The projected climate changes are expected to induce large shifts from cereals to annual industrial crops in the two rice bowls of the country.

1.3. Overview of data and research methods

In what follows we present a brief description of the data used, the methods applied in our studies. More details about the data and the methods are discussed in consecutive analyses from Chapter 3 to Chapter 5.

All the data used in our studies are secondary. We make use of the nationally representative surveys – the Vietnam Access to Resources Household Surveys (VARHS) from 2006 to 2016. These surveys have been conducted by the Vietnamese government once every two years since 2006 to give extra information on access to resources by rural households. The VARHS 2006 collected information on 2,324 rural households in 12 provinces across seven agro-ecological regions. Most of these households were then re-surveyed in subsequent rounds while the sample sizes have been adjusted to population growth. These datasets contain rich information on agricultural production and access to markets. These surveys provide an opportunity to generate panel data which are believed to enhance the robustness of econometric results. We applied the Probabilistic Data Record Linkage method to combine separate datasets to generate panel data:

First, different data files in each year were linked together by using the probabilistic record linkage (reclink2 command in Stata). Identifiers used for the linkage technique are province code, district code, commune code, and household code.

Second, the linked dataset for each year was then cleansed to retain households with agricultural production. The second step reduced sample size in each year substantively. After data cleansing, we have 2,103, 2,381, 1,883, 1,839, 1,537 and 1,628 households for the years 2006, 2008, 2010, 2012, 2014, and 2016, respectively. These data files were then cleansed again to give them identical structure.

Finally, these separate datasets were appended together to make a ten-year panel using the same identifiers as what were used in the Probabilistic Data Record Linkage. For the technology adoption and its impact assessments (Chapter 3), we are interested in creating a balanced panel for the period 2006-2016. Therefore, we dropped out all households without rice production and all households with missing values for any given year were removed from the panel. We have a strongly balanced panel of 325 households with complete information surveyed in all years in the study period, or a total of 1.950 year-observations. However, for the analysis of climate impact assessment in Chapter 4, we use a larger unbalanced panel of more than 8,000 year-observations. Chapter 5 ignores the panel structure of the data. We pool the data across years and allowed time-effects in the Fractional Multinomial Logit model. Therefore, the Fractional Multinomial Logit model in Chapter 5 is estimated on a data frame of 11,829 year-households.

The climate impact assessment in Chapter 4 and Chapter 5 uses climate normals of temperature and rainfall for the period 1970-2000. The climate data with a high resolution of one square kilometer were derived from Worldclim version 2.0. Climate and agricultural production may vary across latitudes (Mendelsohn *et al.*, 1994). We extract data on elevation with the same resolution using free spatial data from DIVA-GIS website. These climate and topographical data were extracted with the kind assistance of Ha Nam Thang at the Environmental Research Institute of the University of Waikato. The climate and elevation data were then matched with the household location.

For the estimation of productivity impacts of hybrid rice in Chapter 3, we apply a True Fixed-Effects (TFE) panel stochastic frontier model on a matched sample generated from Propensity Score Matching to address selectivity bias. The Propensity Score Matching is applied to generate a subset of observations with similar pairwise probability towards hybrid rice seed adoption. The TFE frontier model is then applied on the subsample. The Propensity Score Matching eliminates selection on observables. The TFE estimators are free from unobserved time-invariant heterogeneity. Unobserved time-varying heterogeneity is uniform between the two groups of farmers with different adoption status and is not a source of bias. Previous impact assessments in the rice sector failed to accommodate direct comparisons of the base productivity and factor productivity. We adopt a flexible Stochastic Frontier model that allows for disentanglement of technology and managerial gaps. We also relax the assumption on time-invariant technical efficiency using the panel stochastic frontier model developed by Greene (2005).

The assessment of economic impacts of climate change in Chapter 4 applies the Ricardian approach to an unbalanced panel over ten years. Prior panel Ricardian analyses have captured market variations as common shocks (Blanc & Schlenker, 2017; Blanc & Reilly, 2017). However, variations in agricultural commodities are not uniform (Haile *et al.*, 2016) such that farmers with production of different crops may be exposed to different market shocks. We relax this assumption to capture heterogenous market feedbacks across households in different regions. The Ricardian function is estimated across 20 crops that have been typically produced in Vietnam. We carefully test for stability of climate effects in the period studied to justify the use of the two-stage Hsiao method. The dependent variable is net crop income per square meter. The independent variables represent a broad range of factors potentially associated with agricultural performance, including household characteristics, farmland characteristics, socio-economic conditions, and climate. In the first stage, the dependent variable is regressed on time-varying variables to obtain the residuals. These time-mean residuals (simple residuals plus fixed-effects) are then regressed upon climate variables, along with other time-invariant controls. The Hsiao method is used to simulate the likely impacts on Vietnam agriculture of marginal and non-marginal changes in long-term climate.

The analysis on the sensitivity of the Vietnam land use choice in Chapter 5 employs the Fractional Multinomial Logit model. The advantages of the Fractional Multinomial Logit model over the Multinomial Logit model are that this approach allows the estimation of land use with a set of more than one dependent variables representing different land use shares for different crops. In addition, the interpretation of the Fractional Multinomial Logit model based on the average marginal effects is easy to understand. We regress the set of dependent variables (which are land use shares of different crops) on a broad range of factors which are potential drivers of land use allocation, including a set of climatic variables and their square terms (in addition to climate interactions). In order to obtain a sense of climate change impacts on land use choice, we simulate how the projected climate changes will alter Vietnam land use in the future using the Fractional Multinomial Logit results. Figure 1.1 presents the core elements of the thesis and how they fit together in a framework.

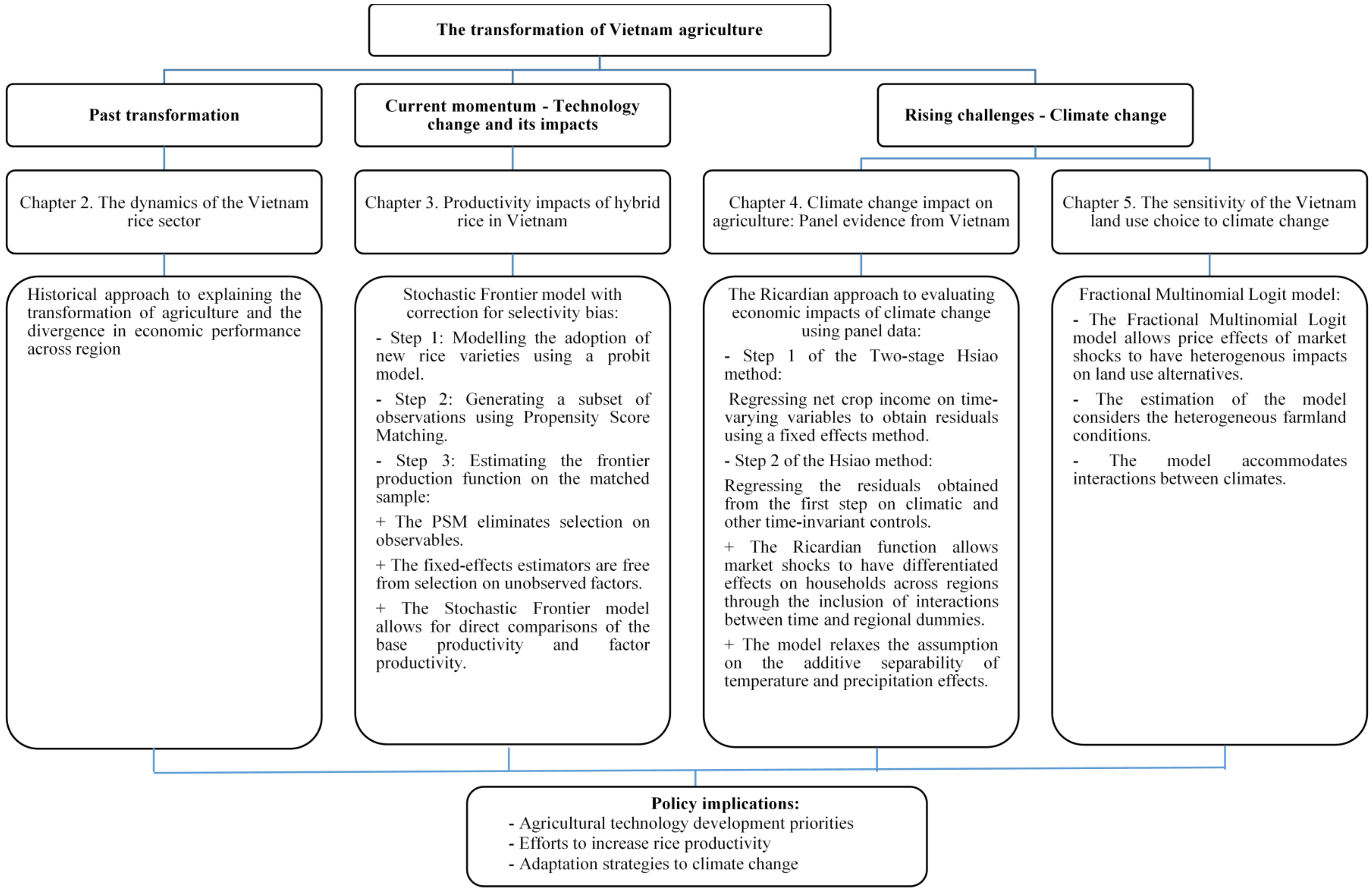

Figure 1.1. Conceptual framework of the thesis

1.4. Contributions to the literature

This thesis is a compilation of four interrelated studies aiming at shedding light on the dynamics of Vietnam agriculture under changing conditions. Each of the studies focuses on different aspects of agriculture. The thesis fills knowledge gaps pertaining to economic issues and econometric modelling methods.

The first study in Chapter 2 provides a comprehensive overview of the transformation of Vietnam agriculture and its changing context in the latter half of the twentieth century. Although the fast improvement in Vietnam agriculture has been documented, barely any previous studies have systematically and adequately examined the sources of the transformation. This study explains the Vietnam agriculture transformation as a result of technical change, and policy change. In addition, researchers have been finding a growing discrepancy in agricultural performance in favor of the Mekong River delta over the Red River delta. This analysis, however, provides evidence that this received view is no longer sustainable.

The second study in Chapter 3 makes several contributions to technology impact assessment in the rice sector. Firstly, it is among the first to examine how adoption of hybrid rice varieties affect farm productivity and technical efficiency measures using panel data. Our panel estimates on the matched sample from PSM show that the fixed-effects estimators can eliminate selection on unobservables as long as they are time-invariant or uniform across groups of farmers. Secondly, we propose a simple way to accommodate for direct comparisons of the base productivity which is irrespective of input application rates (Barrett *et al.*, 2004), and factor productivity differences between rice seed technologies in a stochastic framework. Finally, in contrast to the common findings on positive impacts of hybrid rice seeds, this analysis documents a negative impact of hybrid rice seeds in Vietnam between 2006-2016. The analysis is, therefore, important when seeking to draw policy implications regarding rice technology in the post-Green Revolution period.

The third analysis in Chapter 4 makes one important contribution to the existing literature on climate impact assessment. Prior panel Ricardian models have assumed agricultural market variations to be common shocks to all households. Our panel Ricardian model allows for heterogeneous price feedbacks across regions with different crop choices. We also relax the assumption of the additive separability of climate effects. Our results demonstrate that while assuming homogenous market shocks biases climate estimates, the likely consequences of ignoring climate interactions is severely misleading. Our climate impact simulation documented marginal losses due to the projected changes in long-term climate.

The fourth empirical analysis in Chapter 5 is the first climate-induced adaptation analysis in Vietnam. It is also the first climate-induced crop choice model which has taken into account differentiated market shocks to different land use alternatives. Modelling land use choice is complicated due to several constraints on the choice of crops for a particular farmland plot. We consider the heterogeneity of farmland characteristics in the Fractional Multinomial Logit model by clustering the model by household. Hypothesis tests confirmed the significance of accounting for heterogeneous market shocks in explaining climate-induced adaptation when modelling the sensitivity of land use choice. The allocation of farmland in Vietnam is found to be sensitive to climatic conditions which is in line with empirical findings for China (Wang *et al.*, 2010), Germany (Chatzopoulos & Lippert, 2015), South America (Seo & Mendelsohn, 2008), and Africa (Kurukulasuriya & Mendelsohn, 2007). Seasonal climates exert heterogeneous impacts on land use shares for different crops. The simulation indicates large shifts in areas allocated to cereals towards annual crops between 2030 and 2100.

1.5. Thesis outline

The rest of the thesis is organized as follows:

Chapter 2. An agro-economic history of the Vietnam rice sector

Chapter 3. Productivity impacts of hybrid rice seeds in Vietnam

Chapter 4. Measuring the impact of climate change on agriculture in Vietnam: A panel Ricardian analysis

Chapter 5. Farm-level adaptation to climate change in Vietnam: Investigating the uptake of crop substitution

Chapter 6 concludes the dissertation.

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Chapter 2. An agro-economic history of the Vietnam rice sector

Abstract. The Vietnam economy and its agriculture have undergone intensive transformation since the reforms in the late 1980s. From a devastated country with barely any prospect for development, Vietnam transformed into a developing country with high annual growth rate and fast reduction in headcount poverty. Agriculture has been important as it employs a large portion of the rural population. Researchers have found the faster development of rural South economy, relative to the North. This paper employs an historical approach to explaining the transformation of Vietnam agriculture, with an emphasis on the rice sector. It argues that in contrast to common perceptions, the rural North, and particularly the Red River delta, outperformed the Mekong river delta in terms of rural income despite the disproportionate distribution of reform effects due to limited landholdings. Future sustainable development of the agriculture depends on how it overcomes the negative impacts of changing climate and market uncertainty. The development of the Red River delta agriculture is facing additional challenges due to limited land endowments and inherent land fragmentation.

Keywords: history, Vietnam, rice, transformation, Red River delta, Mekong River delta

2.1. Introduction

The on-going success of the agricultural sector has been attributable to the fast and steady economic performance of Vietnam. In the early 1980s, Vietnam was one of the five poorest countries with a gross domestic product (GDP) per capita of about US$130 per year (Glewwe, 2004). The economy was characterized by a centrally planned system with barely any markets. Rice yield stagnated at around 2 tons per hectare while rice output per capita decreased down to the lowest point since 1955. After a series of reforms in the late 1980s, Vietnam emerged as a rice exporter. At the same time, the agricultural share of GDP declined from 34% in 1985 to approximately 16% in 2016 (General Statistics Office [GSO], 2016b). The annual agricultural growth of 4.8% (OECD, 2015) and equitable income distribution resulted in a fast reduction in headcount poverty in rural areas, from 70% in 1993 to 10% in 2006 (McCaig *et al.*, 2009). At the national level, total income per capita increased by 17.3% per annum while income from crop production increased at a rate of 12.3% per annum in the period 1993 - 2014 (General Statistics Office [GSO], 2016a; State Planning Committee & General Statistics Office, 1994).

Several researchers have tried to explain the impressive performance of the Vietnam economy and its agriculture. Reform policies during the decades have been attributable to the overall economic transformation (Glewwe, 2004). The decollectivization (Pingali & Xuan, 1992), and agricultural technology (Ut & Kajisa, 2006) had positive impacts on agricultural productivity. The liberalization of domestic markets and removal of export barriers resulted in higher rice prices, lower imported fertilizer cost (McCaig *et al.*, 2009; Brandt & Benjamin, 2002), and decreased spatial output prices (Brandt & Benjamin, 2002; Goletti, 2000). However, spatial differences exist between the rural North and the rural South economies. The rural North-South income ratio decreased from 0.87 in 1993 to 0.79 in 2006 (McCaig *et al.*, 2009).

Although several researchers have found the divergence in economic performance across regions (McCaig *et al.*, 2009; Minot *et al.*, 2006; Brandt & Benjamin, 2002), the literature on the driving forces of the differences has been scarce. Jerez (2018) argued that the smallholdings and excessive land fragmentation in the Red River delta resulted in stagnant agricultural practices in which farmers live on subsistence farming without real income growth, relative to the transformative Mekong River delta. However, the author's opinions on the economic performance of the two deltas are misleading as they are drawn from the data for the North and the South as a whole, not for the two deltas.

This chapter applies an historical approach to explaining the transformation of Vietnam agriculture with an emphasis on the rice sector. It argues that the impressive performance of the agricultural sector has been the outcomes of policy, institutional, technological, and infrastructural changes. Despite the disproportionate distribution of reform effects due to different land endowments, farmers in the Red River delta outperformed their counterparts in the Mekong River delta in terms of income growth. In addition to the faster increase in salary, agricultural incomes in the Red River delta have improved more than what Jerez (2018) and other researchers have argued. The sustainable success of Vietnam agriculture depends on how it overcomes the emerging challenges.

2.2. The dynamics of the Vietnam rice sector

2.2.1. Agricultural performance

Vietnam has undergone a fundamental transformation from a centrally planned economy to a regulated market one since the Doi Moi[1] initiated in 1986. In the early 1980s, Vietnam was one of the five poorest countries with low economic growth and high inflation (Glewwe, 2004). With a series of policy changes in December 1986, Vietnam transformed itself into one of the most successful countries in the world in terms of economic growth, poverty reduction and increased household welfare (McCaig *et al.*, 2009; Glewwe, 2004).

While maintaining a high economic growth of more than 5% per annum in the period 1990 - 2015, Vietnam has been achieving a substantial reduction of the relative weight of agriculture to manufacturing industry, from 36% in 1986 to 16% in 2016. In comparison with other Asian countries with similar economic conditions in the 1980s, Vietnam's agricultural performance outperformed Thailand, Malaysia, the Philippines, and other selected countries in the period 1981 - 2019.

[1] The comprehensive reform proposed in the Sixth Congress of Vietnamese Communist Party in 1986 which shifted the Vietnam economy from a centrally planned to a regulated market economy.

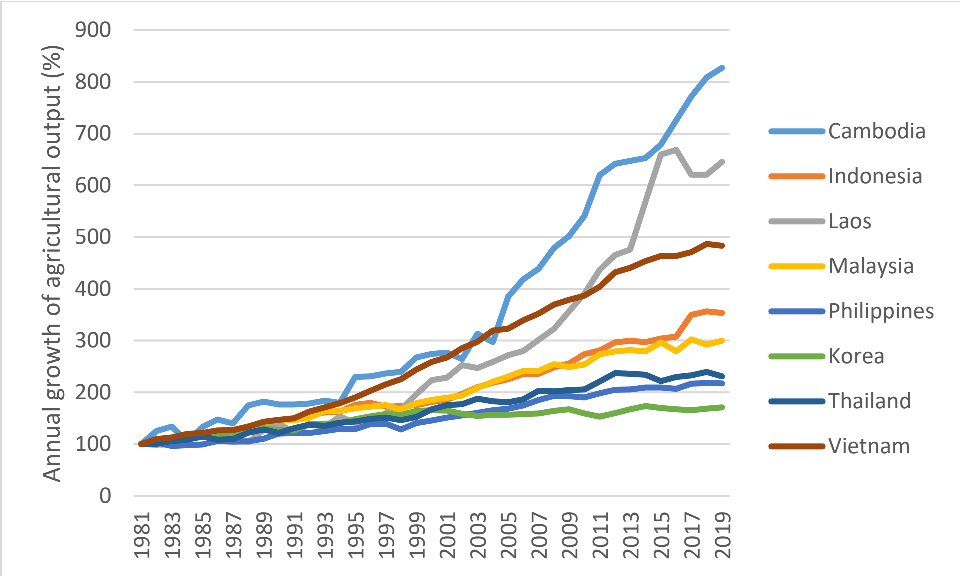

Figure 2.1. Growth in agricultural production in selected countries, 1981 - 2019

Source: FAO stats database online

With a large proportion of the population engaged in agriculture, improvements in agricultural productivity and rural household incomes played a pivotal role in economic growth and equity. Rural household income rose by 11% per annum in the period 1993 – 1998 (Brandt & Benjamin, 2002), and by 7% per annum for the period 2002 - 2014 (Benjamin *et al.*, 2017). Although there have been differences in income growth across regions, income inequality, measured by the Gini coefficient, decreased from 0.45 in 1993 to 0.36 in 2014 (Jerez, 2018; Benjamin *et al.*, 2017). The main reasons for the increase in household incomes were increased earnings of agricultural workers (Benjamin *et al.*, 2017; Ravallion, 2008) and off-farm job opportunities (Benjamin *et al.*, 2017). Agricultural population decreased from 70% in 1990 down to 44% in 2015 indicating the constant release of labor out of agriculture. However, agriculture remains important in the Vietnam economy.

2.2.2. Rice production and agricultural technology change during the decades

Rice plays a pivotal role in Vietnamese agriculture as it accounts for more than 60 percent of the total annual cropping area (GSO, 2016b). The development of the rice sector, therefore, has been crucial to the transformation of rural Vietnam. Apart from maintaining food security, rice exports have been the engine of economic growth of the country. However, Vietnam agriculture, and particularly the rice sector, has undergone fluctuations which were partly a result of the historical production system.

Prior to the Reunification in 1975, the North underwent a collectivization process in which peasant families belonged to a cooperative while the South maintained private agriculture. The whole country experienced increases in rice production of 2% in the period 1950 - 1965. In the South, the Land to The Tiller program (Prosterman, 1970) resulted in increases in both rice area and yield for the period 1966 - 1975. On average, total area under rice cultivation increased at an annual rate of 3.18% while rice yield increased by 2.31%. In the North, the collectivization of agriculture resulted in less economic incentives for farmers (Pingali & Xuan, 1992) which in turn reduced the rice area by 0.24% per annum.

The Reunification in April 1975 marked the collectivization in the whole country although it was weak in the South. While 99.4% of Northern farmers were members of an agricultural cooperative in 1986 (Pingali & Xuan, 1992), the collectivization of agriculture in the Mekong delta encountered resistance from peasants. Only 6% of farmers in the Mekong delta joined high-rank cooperatives. The collectivization of production and inappropriate output distribution based on working hours led to decreases in both rice area and yield. In the North in the period 1976 - 1981, rice area decreased by 0.26% per year while rice productivity decreased at a faster rate, 3.87% (Che *et al.*, 2006). The country experienced a sharp decrease in rice availability. Rice output per capita decreased from 280 kilograms in 1960 to about 220 in 1980 (Pingali & Xuan, 1992). Vietnam had to import rice while a significant proportion of farmers left their cooperative or left their land fallow.

Facing food deficits in the North, the Central Politburo of the Communist party issued the Directive 100 CT in April 1981. This Directive shifted the collectivization of agriculture into a new form – the farmer contract system, which was analogous to the

Household Responsibility System in China in the late 1970s. Farmers were assigned to supply their cooperative an amount of output proportional to their land and labor while the provision of inputs and labor was furnished by the cooperative. Farmers had more control over their production and more incentive to work harder. This contract system had a positive impact on food production. Aggregate rice output in the period 1982 - 1987 increased by 3.77% per annum in the North and by 4.58% in the South.

Table 2.1. Rice production, North and South Vietnam

Time period	Growth in cultivated area per annum (%)	Growth in yield per hectare per annum (%)	Growth in total rice production per annum (%)	Population growth rate (%)
Vietnam				
1950-1955	2.79	-0.74	2.05	2.05
1956-1965	0.33	2.30	2.63	2.72
1966-1975	1.59	2.22	3.80	3.10
1976-1981	1.14	0.82	1.91	2.60
1982-1987	0.08	2.73	2.81	2.60
1988-1994	2.35	3.14	5.56	2.07
1995-2011	0.78	2.57	3.37	1.07
2012-2019	-0.54	0.45	-0.09	1.19
North Vietnam				
1950-1955	0.22	0.74	0.90	n.a
1956-1965	0.85	-0.16	0.66	2.40
1966-1975	-0.24	1.82	1.59	2.09
1976-1981	-0.26	-3.62	-3.87	n.a
1982-1987	-0.12	3.89	3.77	n.a
1988-1994	-0.60	6.03	5.40	n.a
1995-2011	-0.08	2.74	2.66	n.a
2012-2019	-0.95	0.15	-0.80	1.40
South Vietnam				
1950-1955	5.63	-2.06	3.59	n.a
1956-1965	-0.13	4.81	4.64	3.30
1966-1975	3.18	2.31	5.48	3.80
1976-1981	-1.08	4.56	3.43	n.a
1982-1987	-1.77	6.46	4.58	n.a
1988-1994	-0.51	7.09	6.55	n.a
1995-2011	1.21	2.47	3.72	n.a
2012-2019	-0.37	0.57	0.21	1.01

Note: n.a: Data not available

Sources: All data for the whole country in the period before 1990 and the two regions before 1976 were taken from Pingali and Xuan (1992), data for the period 1990-2016 were taken from Statistical Yearbooks (various years). Other information in the table was taken from Che *et al.* (2006).

The further privatization of agriculture in 1988 and liberalization of agricultural markets had positive impacts on rice production and farmer welfare. Private land use entitlement gave farmers full control over production while the improvements in the rice market and input supplies resulted in higher income from production. In the early stage of the reform, from 1988 to 1994, both regions experienced decreases in rice areas, but average rice yield increased at a rate of 6.03% and 7.09% for the North and the South, respectively. At a national level, total rice production in the period 1995 - 2011 increased by 3.37% per annum in which improvement in rice yield made up the largest part. Rice production witnessed declines in the period 2012 – 2019 as a result of both declines in rice areas and yields in the two regions. This trend is contrary to the rising application of hybrid rice seeds and intense input levels in the same period.

Undoubtedly, the reforms contributed to the expansion of agriculture by strengthening land use rights and farm management autonomy, and by improving the efficiency of market operation. However, the continuous introduction and adoption of improved agricultural technologies has also been identified as a driver of Vietnam agriculture. The high yielding variety IR8 developed by the International Rice Research Institute was introduced into Vietnam in 1968. Its average yield was 4 tons per hectare, far higher than the yield of traditional varieties of 2 tons per hectare. This modern variety was soon accepted by southern farmers as the adoption rate increased from 1% in 1968 to 33% in 1975 (Ut *et al.*, 2000). In the North, under a different name of NN8, this new seed was also welcomed. Until the early 1970s, nearly 50% of the cultivated area in the North was under NN8 variety (Xuan, 1995).

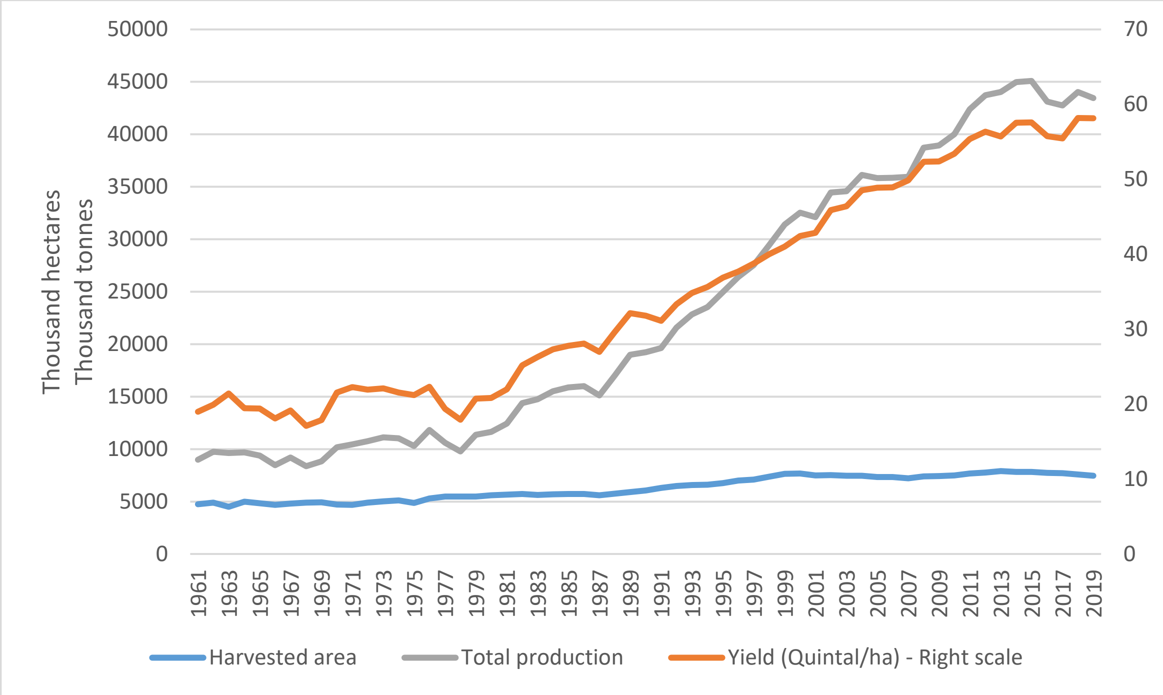

Figure 2.2. Rice yield, production and harvested area in Vietnam, 1961-2019

Source: FAO stats database online

The growth of rice production since the early 1980s to 2015 was remarkable. Rice yield increased from 3 tons per hectare in 1985 to 3.5 tons in 1993 before reaching a high of 5.8 tons in 2018. Total rice production increased dramatically from 30 million tons in 2000 to 45 million tons in 2015. The increase in rice yield over the period was associated with the rising application of improved seeds and chemical fertilizers. The country experienced a boom in the use of modern varieties as the adoption rate increased from 16.9% in 1980 to more than 94% in 2002 (Table 2.2). The constant release of modern varieties in the past few decades kept the momentum for the Vietnamese Green Revolution going.

Table 2.2. Adoption of improved seed varieties by ecological region

	Whole country	Red River delta	Mekong River delta	Northern Highlands	North Central	South Central	Central Highlands	Southeast
1980	16.9	52.9	9.7	4.7	10.1	17.3	2.3	9.3
1985	28.5	68.4	26.4	6.4	11.8	23.0	9.8	16.3
1990	47.5	78.5	48.3	30.8	17.6	47.6	44.3	41.3
1995	76.2	90.5	79.8	63.8	62.0	60.8	75.2	79.7
1998	87.2	92.2	87.7	81.2	87.1	81.9	83.0	91.3
2002	94.2	96.3	99.5	84.5	87.1	88.2	77.2	87.6

Source: Ut and Kajisa (2006). Data on farmland allocated to different rice varieties are not available after 2002.

The removal of fertilizer import barriers contributed to the rising application of chemical fertilizers in rice intensification. In the period 1980 - 2005, the use of chemical fertilizers rose steadily from more than 50kg/ha to 160 kg/ha. Despite a slight decrease in the application in the period 2005-2010 due to escalating prices, chemical fertilizer application increased dramatically from 160kg/ha in 2010 to 230kg/ha in 2015 as a consequence of lower import prices (OECD, 2015).

Along with technology changes, farming techniques have also been modified to adapt to changing conditions. The constant release of new seed varieties with shorter growth periods resulted in higher cropping intensity (Agrifood Consulting International, 2002). In the South where the climate is more favorable, triple cropping is common while large farming plots resulted in a widespread of broadcast seeding. As a result, farmers in the Mekong River delta use more seeds than those in the Red River delta (Agrifood Consulting International, 2002). Manual transplanting has been the traditional farming technique in the Red River delta. Consequently, the Red River delta remains a labor-intensive agriculture.

2.2.3. Rice marketing

Prior to the market reform in the early 1990s, the private sector was the main sector involved in agricultural production while the marketing of rice was restricted and characterized the State utilizing buying and selling cooperatives (Pingali & Xuan, 1992). Export of rice was restricted by export quotas and licenses while movement of rice from the South to the North had to undergo procedures similar to export (Goletti, 2000). Rice output was to be sold to the State with a price of 20% - 30% of market price (Che *et al.*, 2006). A centrally planned system with barely any markets resulted in the stagnation of Vietnam agriculture (Che *et al.*, 2006; Pingali & Xuan, 1992).

During the early phase of market liberalization, the private sector was encouraged to participate in the marketing of rice. However, rice export was still subject to barriers as State-owned enterprises (SOEs) were the only participants in rice exporting (Ghoshray, 2008). There exist huge gaps in size and assets between SOE and the private sector in the rice marketing chain. On average, a SOEs had an asset value of US$1,594 thousand while the number for private traders and millers was 3 thousand and 31 thousand, respectively (Goletti, 2000, p. 11). However, the private sector was responsible for collecting, moving and distributing of 80 percent of rice produced in Vietnam.

The further liberalization during the 1990s resulted in the removal of barriers to export and domestic trade (Resolution 140/1997/QĐ-TTg on 3/1997). Improved infrastructure across regions has given rise to local private traders. Therefore, the Vietnam rice marketing system is characterized by a complex web of relationships among agents. These relationships create different marketing channels. The main difference in marketing of rice in the Red River delta and the Mekong River delta is the consumers. Most of the rice surplus in the Red River delta is distributed domestically to other regions with rice deficit. Rice marketing in the Mekong River delta is export-oriented (Goletti, 2000).

The liberalization of the rice market resulted in an increase of 30% in farmgate rice prices between 1993 and 1998 (Niimi *et al.*, 2007). Despite institutional and infrastructural improvements in rice marketing, imperfections in the rice marketing system still exist. Large and consistent market margins reflect unexplained differences in rice prices across regions. In perfect markets, price differences across regions must be equal to transport costs (Goletti, 2000; Minot, 1997). Minot (1997) found a 709 Vietnamese dongs difference in price per kilo of rice between the North and the South while transport cost just accounted for 42% of the margin. Goletti (2000), Agrifood Consulting International (2002), and Minot (1997) also documented no apparent trend in marketing margins of rice in Vietnam indicating no signs whether it would decrease. The plausible explanations for high price differences have been domestic trade barriers (Minot, 1997), ineffective operations of private traders (Agrifood Consulting International, 2002; Goletti, 2000), and local nature of the marketing information.

Table 2.3. Regional rice prices during the early phase of the reform

Year	Average wholesale price (VND/kg)		
	North	Central	South
1986	4,257	4,257	4,470
1987	7,254	6,385	6,334
1988	6,622	5,531	4,678
1989	5,614	5,066	4,612
1990	6,770	6,243	4,711
1991	6,116	5,129	4,406
1992	4,678	3,965	3,814
1993	3,964	3,473	3,460
1994	3,508	3,283	2,934
1995	4,022	3,451	3,045
1996	4,392	3,703	2,901

Source: Minot (1997) (Prices are deflated to 2000 using GDP deflator from FAO stats database online)

The imperfect nature of the Vietnamese rice marketing system is also reflected in profitability across marketing agents. Although farmers in the Red River delta received a higher share of retail price than their counterparts in the Mekong River delta (83% versus 71%), they got lower profits ($57 per ton versus $93 per ton) due to higher production cost (Goletti, 2000). Marketing agents in the Mekong River delta also got higher profits than those in the Red River delta despite their lower share of their marketing margin in retail price. On average, the unit profit of marketing agents in the Mekong River delta was US$55 per ton (18% of retail price) while the number for marketing agents in the Red River delta is US$34 (11% of retail price) (Goletti, 2000).

The removal of rice export quotas and licenses resulted in an asymptotic trend of domestic prices to international prices. However, fluctuations in international prices are partially transmitted into domestic prices reflecting the under-integrated nature of the Vietnam rice sector. Only 11% of price variations in the world rice market is transmitted to domestic prices while the number for Bangladesh and Pakistan is 74% and 41%, respectively (Robles, 2011). In addition, price shocks are slowly transmitted from one separate market to one another. It normally takes 2.6 months in Bangladesh or 3.53 months in Egypt for a price shock to be transmitted to another market (Minot, 1997). In Vietnam, it may take up to 5.15 months (Minot, 1997). The low integration of the Vietnam rice markets reflects the local nature of rice marketing system and policy insulation from the world food market.

2.2.4. Rice exports and imports

The land reform in 1989 had an immediate impact on rice production and export. After more than two decades of rice deficit, Vietnam exported more than 1 million tons of rice in 1989. However, the constraints on rice production still existed in the early stage of the reform. The further liberalization of output market and rice export resulted in the removal of export quotas while private enterprises also played their part in the export of rice. In the period 2001-2016, the export volume maintained an annual average of more than 5 million tons.

Table 2.4. Average annual level of rice exports/imports during each period (1000 tons)

Period	1950-1964	1965-1981	1982-1988	1989-2000	2001-2016
Export volume	160.00	9.90	84.57	2,500.00	5,073.40
Import volume	n.a	620.60	271.60	6.90	6.60
Net export volume	n.a	-610.70	-187.03	2,493.10	5,066.80

Source: Data for the period 1950-1964 were taken from Dawe (2002); data for other periods taken from FAO stat online database

The world rice market is thin with only 6% of total production being traded (Chen & Saghaian, 2016). Most of rice exports are from six countries, namely Thailand, Vietnam, the U.S, China, India, and Pakistan. Thailand is the largest exporter of rice with an average of 40% - 50% of production being exported. Vietnam became the second largest exporter of rice, with an average of 5 million tons per year. Most of Vietnam rice exports are to other Asian countries. Given the thinness of the world rice market, exporters of rice may benefit from large transactions and market manipulation (Chen & Saghaian, 2016). However, Vietnam export prices are still low despite its share of 15% of the world rice exports. In 1990, export prices for Vietnam high-quality rice (5% broken) were 37% below Thai prices (Chen & Saghaian, 2016).

Policy interventions were found to strongly affect both export quantity and price transmission. As rice is the most important calorie intake for domestic consumers (Agrifood Consulting International, 2002), price stabilization and insulation from world rice market shocks is considered necessary. Since the world food shock in 2007/2008, rice exports have been restricted to assure domestic food security (Resolution No. 63/2009/NQ-CP on food security dated 23 December 2009). Although Vietnam rice prices are cointegrated with Thai prices (Jamora & von Cramon-Taubadel, 2017; Chen & Saghaian, 2016), changes in export prices are slowly transmitted to domestic prices (Robles, 2011; Agrifood Consulting International, 2002).

Nghiem and Coelli (2002) estimated an annual growth of 3.3 percent in the rice sector between 1976 and 1997, which was above average agricultural productivity growth in other developing countries (Fulginiti & Perrin, 1998). However, there have been spatial differences in agricultural performance as Southern farmers were found to be better than their Northern counterparts at taking advantage of new opportunities offered by the reforms (Jerez, 2018; Benjamin *et al.*, 2017; Brandt & Benjamin, 2002). The next section will discuss the differences in initial conditions (land endowments and wealth) while the following two sections focus on how these initial conditions affected the divergence of the two river deltas.

2.3. Regional differences in initial conditions

Despite fundamental institutional reforms during the decades, the differences in factor endowments across regions remain unchanged which, in turn, posed different barriers to transformation for each region. It is important to understand the differences in initial conditions in order to explain the growing differences across regions.

The Red River delta experienced higher increases in rice productivity in the period 1990 – 2016. However, Che *et al.* (2006), Kompas (2004), and Nghiem and Coelli (2002), among others, found the increases in total productivity were positive in the South while they were negative in the North. They suggested that the differential incentives between the two deltas might lead to different responses. Jerez (2018) explained the differences between the two river deltas as a result of differentiated land endowments. Particularly, the smallholdings and excessive land fragmentation in the Red River delta resulted in a high-level equilibrium trap in which farmers produce at subsistence levels. The small endowments made the Red River delta a labor-intensive agriculture with diminishing returns to labor while the excess of labor did not leave the agriculture. This section contrasts the differences in farming land and household incomes over time to support a viewpoint of a more transformative Red River delta than what Jerez (2018) considered.

Table 2.5. Farming land characteristics in the two river deltas

Year	1992	2002	2006	2010	2012	2014	2016
1. Red River delta							
Household size	4.2	4.0	3.8	3.7	3.6	3.6	3.9
Farm size (m^2)	2,800	n.a	1,931	2,180	1,922	2,816	1,462
Number of plots	n.a	n.a	5.8	5.1	4.7	4.2	3.7
Average area of each plot	n.a	n.a	331	430	404	618	360
2. Mekong River delta							
Household size	5.4	4.6	4.3	3.9	3.9	3.8	4.0
Farm size	11,050	n.a	10,717	14,697	14,745	19,170	5,700
Number of plots	n.a	n.a	2.9	2.9	2.9	2.6	2.7
Average area of each plot	n.a	n.a	3,674	5,048	4,161	4,500	2,500

Note: n.a: Data not available

Source: State Planning Committee and General Statistics Office (1994); (GSO, 2016a); (CIEM, 2015)

Table 2.5 shows an increase in farming land per labor in the Mekong River delta between 1992 and 2016. The Red River delta has been densely populated, with a population density of over 1000 persons/km^2 in colonial time under the French rule. The area under rice cultivation remained unchanged since 1960 (626,000 hectares arable and 1 million hectares cultivated) (Jerez, 2018). The average landholding in 2016 was 1.400m^2, equivalent to 25% of that of their counterparts in the Mekong River delta. The effects of inheritance and household division made land become increasingly fragmented during the century. It was estimated that there were 16 million parcels in 1937, with less than 0.089 hectares per parcel on average. This number increased up to 17 million in 1941 (Jerez, 2018). A typical peasant family in the Red River delta cultivates on 3.7 separate parcels with each parcel averaging 360 m^2 in 2016.

The consequences of excessive fragmentation have been documented in the literature (Barrett, 1996; Feder, 1985; McPherson, 1982; Sen, 1966). Land fragmentation causes difficulty in rationalizing production cost and reduces efficiency of labor. It hinders the adoption of mechanization (Orea *et al.*, 2015; Pannell *et al.*, 2006). In addition, it deters the release of excessive agricultural labor to other sectors (Jia & Petrick, 2014; Kawasaki, 2010). With a limited farming land, agricultural surplus in the Red River delta is less than that of their counterparts in the Mekong River delta. In 2014, the portion of output sold by farmers in Ha Tay province was just 25%, relative to nearly 40% in An Giang province of the Mekong delta (CIEM, 2015). However, in contrast to common perceptions, farming households in the Red River delta have been doing better than those in the Mekong River delta in terms of income generation.

Due to data constraints, this section focuses on the income evolution in the two river deltas during the two decades after the reforms. The heavy dependence on agriculture in the early stage of economic transformation was reflected in the income structure across regions. Income from crop production accounted for roughly 40% of total income in 1992 for both regions. The less developed Northern economy was reflected in a smaller proportion of income from wages in the Red River delta. On average, income from wageworkers accounted for just 16.6% of total income for a rural household in the Red River delta while the number for those in the Mekong River delta was 22.9%. With little land endowments and less off-farm job opportunities, rural households in the Red River delta diversified income activities from sidelines which made up 36.5% of total income.

Table 2.6. Income structure of rural households in the two river deltas

Period	1992	2002	2008	2014	Annual growth rate 1992-2002	2002-2008	2008-2014	1992-2014
I. Monthly income per capita (1000 VND)								
1. Red River delta								
Total	91.3	353.1	1,048.5	3,277.5	16.2	19.9	20.9	18.6
Crop	36.5	80.2	173.9	297.5	9.2	13.8	9.4	10.5
Sidelines	33.3	91	259	764.9	11.8	19.0	19.8	16.1
Wage	15.2	118.5	397.2	1,742.1	25.7	22.3	27.9	25.4
Other incomes	6.3	63.4	218.4	473	29.1	22.9	13.7	22.8
2. Mekong River delta								
Total	105.4	371.3	939.9	2,326.8	15.0	16.7	16.3	15.9
Crop	42.9	100.8	281.1	491.5	9.9	18.6	9.8	12.3
Sidelines	35.4	126.5	279.6	710.5	15.2	14.1	16.8	15.4
Wage	24.1	92.7	244.4	783.2	16.1	17.5	21.4	18.0
Other incomes	3.0	51.3	134.8	341.6	37.0	17.5	16.8	25.3
II. Income structure (%)								
1. Red River delta								
Crop	39.9	22.7	16.6	9.1				
Sidelines	36.5	25.8	24.7	23.3				
Wage	16.6	33.5	37.7	53.1				
Other incomes	7	18	21	14.5				
2. Mekong River delta								
Crop	40.7	27.1	29.9	21.1				
Sidelines	33.6	34.1	29.7	30.5				
Wage	22.9	25.0	26.0	33.7				
Other incomes	2.9	13.8	14.3	14.7				

Source: State Planning Committee and General Statistics Office (1994); (GSO, 2016a)

In the period 1992 - 2002, despite higher income growth, monthly income per capita of 353.1 units of farmers in the Red River delta was still lower than 371.3 in the Mekong delta. In the period 2002 - 2008, the Red River delta surpassed the Mekong River delta in terms of total income and income growth. On average for the period 1992 - 2014, the annual income growth in the Red River delta was 18.6%, higher than 15.9% in the Mekong delta. Consequently, the income ratio for the Red River delta and Mekong River delta in 2014 was 1.4 although farmers in the Red River delta began with lower income in 1992.

Improvements in incomes for both deltas were pronounced for all components. Crop production made up the largest part of income for rural households in the two deltas in 1992

(40%). Improvements in land productivity, declined input prices and increased in output prices during the market liberalization benefited most farmers. Between 1992 and 2014, income from crop production increased at a rate of 10.5% for farmers in the Red River delta. With better land endowments, and agricultural surplus as a consequence, farmers in the Mekong River delta maintained higher crop income growth, at 12.3%. To 2014, the crop income ratio for the Mekong River delta and the Red River delta was 1.65.

The higher growth rates of other incomes are crucial for the income revolution of the two deltas although they were more impressive in the Red River delta. Crop production declined in its relative term in both regions. The Red River delta experienced a 30.8% cut-off of the share of crop income, from 39.9% in 1992 to 9.1% in 2014. In the meantime, income from sidelines and wages maintained higher growth rates to become the two most important sources for this delta. These movements remarked the release of excessive agricultural labor. To 2014, wages accounted for more than half of total income for rural households in the less endowed Red River delta while the Mekong River delta experienced just more than 10% improvement in wage share, from 22.9% in 1992 to 33.7% in 2014.

If the Red River delta had been stuck in a stagnant phase as what Jerez (2018) argued, the labor-intensity could not have allowed the release of agricultural labor to other sectors. If the labor had not been released, the income structure would not have undergone such a fundamental change. The more detailed data we have in this paper provide evidence of a more transformative Red River delta than previous thoughts. The next two sections focus on how land endowments affect agricultural outcomes on the two river deltas.

2.4. Land endowments and differential economic incentives

With a limited farming land, farmers in the Red River delta have been working hard to maintain higher income. However, the smallholdings constrained income growth from agriculture. Less agricultural surplus and lower input use exposed farmers in the Red River delta to less incentive from the liberalization of agricultural markets.

2.4.1. Farm size and rice yields

The inverse relationship between farm size and productivity has been investigated extensively in literature so as to answer the oldest puzzle in agricultural economics. Sen (1966) theorized the productivity gap between small peasant and capitalism farms as a consequence of the shadow cost of labor. The lower cost of family labor results in a more labor-intensive production by peasant families. Therefore, small farms are often more productive than large farms in terms of land productivity. Feder (1985) pointed out that hired labors are more intensively used on large farms than on small farms. Because wage laborers tend to shirk if they are not supervised perfectly, larger farms tend to be less productive than smaller farms. Barrett (1996) emphasized that market imperfections make smallholding households oversupply labor on their farms so as to reduce price risks when buying from the market. In contrast, largeholding families who are often net sellers under-supply labor in order to reduce their exposure to price variations when selling to market. Therefore, smaller farmers are more productive than larger farms due to market imperfections.

Table 2.7. Farm size, real wages, and land productivity in the two river deltas

Year	1992	2002	2008	2014
Red River delta				
Average farm size (m^2 per household)	2,800	n.a	1,975	2,816
Average number of workdays per hectare (for rice)	246	n.a	n.a	150
Share of hired labor in production cost (%)	1.57	n.a	n.a	10.80
Agricultural wage (1000 VND/male work day)	7.49	13.59	28.06	128.53
Rice yield per hectare (quintal)	37.71	56.40	58.90	60.20
Mekong River delta				
Average farm size (m^2 per household)	11,050	n.a	12,034	19,170
Average number of workdays per hectare	96	n.a	n.a	55
Share of hired labor in production cost	16.43	n.a	n.a	6.60
Agricultural wage (1000 VND/male work day)	15.01	17.51	25.53	113.26
Rice yield per hectare (quintal)	31.19	46.20	53.60	59.40

Note: n.a: Data not available. Data on agricultural wage are deflated to 1992

Source: State Planning Committee and General Statistics Office (1994); Pingali *et al.* (1997); Barrett (2016); (GSO, 2016a); World Bank Group (2016)

Given the imperfections of rural labor markets in Vietnam in the early phase of the reform, excess labor made the Red River delta the most labor-intensive agriculture within the country. With an average farmland area of 0.2 hectares per household, the number of workdays per hectare in the Red River delta in 1992 was 246 while the percentage of hired labor used in rice production was just 1.57%. Peasant households in the Mekong River delta had larger landholding with an average of 1.1 hectares for the same year. Labor use in rice production was less than in the Red River delta, with an average of 96 workdays per hectare.

During the 1990s and early 2000s, the lack of off-farm job opportunities for rural labor was pervasive indicating low opportunity cost for peasant families. The excessively fragmented land in the Red River delta was a decisive factor contributing to higher labor-intensity with diminishing returns to inputs. Pham (2006) showed that output elasticities to inputs were low while the elasticity to the number of plots was high indicating a potential gain for rice production from land consolidation. Barrett (2016) found the relationship between land fragmentation and labor intensity indicating dual benefits of land consolidation on both labor release and farm profits. However, the inverse relationship between farm size and productivity dampened, especially in areas with higher real wages (Barrett, 2016). In the period 2008 - 2014, the average rice yield in the Red River delta showed little increase while rice yield in the Mekong River delta increased from 53.6 up to 59.4. The rice yield gap between the two river deltas contracted.

Does the decreasing yield gap between the two river deltas reflect better performance of largeholding farmers in the South or worse farmers in the North? Neither answer is complete because farmers in both regions have been doing well. Considering the changes in agricultural wages, the faster increase in agricultural wages is, the slower increase in rice yield is. The fast increase in real wages would dampen the farm size-productivity relationship in the Red River delta. In 2014, rice yields in the two river deltas were similar at around 60 quintals per hectare. The gap in rice yields between the two deltas decreased significantly as a consequence of improvements in the labor markets.

2.4.2. Liberalization of output market

Given the initial differences in local rice markets, the liberalization of output market had different impacts on household welfares. Goletti (2000) estimated a 1.4% decrease in nation-wide rice prices due to the liberalization of the domestic rice market. While the Mekong River delta benefited from a 5.2% increase in rice price, the Red River delta experienced a 9.4% decrease. However, the removal of export barriers resulted in a 25.9% increase in paddy prices Goletti (2000). The combined effect of removing both domestic and export barriers resulted in a 19.9% increase in rice prices.

The income effect of changes in rice prices on households depends on the elasticity of demand and supply, income structure and production scale. For households that were not rice producers, the increase in rice prices resulted in higher expenditure as the elasticity of demand for rice was low. The average price elasticity of demand for rice varied between 0.2 to 0.38 across regions (Goletti, 2000). However, because the majority of the population were engaged in agriculture, increases in rice price due to market liberalization had positive income impact on a large rural population. On average, a 10% increase in rice prices resulted in a 0.8% increase in real income for rice producers.

The Red River and Mekong River deltas had similar proportions of net rice sellers, at around 43% - 45%. Due to smallholdings, net marketable surplus in the Red River delta was quite small, 22%, as compared with 85% in the Mekong River delta. The difference in land endowments for rice production resulted in differentiated gains from the increase in rice prices. Goletti (2000) estimated an average of 0.8% increase in household income due to a

10% increase in rice price for the Red River delta while the number for the Mekong River delta is 1.4%.

2.4.3. Decentralization of input supplies

The allocation of agricultural inputs in the North since 1960, and in the whole country since 1976, was made by the government. This top-down system resulted in an increase in administrative cost and higher input prices. The first stage in decentralizing the input markets was the decentralization of input supplies introduced in 1988. The rising competition among the marketing agents in supplying agricultural inputs resulted in improvements in both quantity adequacy and prices of input markets. Niimi *et al.* (2007) shown a 23% decrease in fertilizer prices between 1992/1993 and 1997/1998 which was attributable to the decentralization of the input supply.

Changes in fertilizer prices affect rice production in several ways. Because chemical fertilizers are an important input in production, reductions in fertilizer prices are associated with lower production cost. In addition, fertilizers are substitutes for labor in rice production. The relative decline in fertilizer prices to the increase in labor wages might encourage the use of fertilizers as a substitute for on-farm labor.

The Mekong River delta agriculture relies more on non-labor inputs relative to a labor-intensive agriculture in the Red River delta. Fertilizer accounted for 42% of total cost in An Giang province (CIEM, 2015) while just 35% in Ha Tay province of the Red River delta. In the period 1993 - 1998, a 23% decrease in fertilizer prices would lead to a 9.6% decrease in total cost for farmers in Mekong River delta. With a smaller proportion of chemical fertilizers in total inputs, farmers in the Red River delta gained an 8% decline in production cost. In addition, the decline in labor use in both deltas is clear in Table 2.7. Although the Red River delta remains a labor-intensive agriculture, the number of workdays per rice hectare decreased from 246 in 1992 to 150 in 2014. The Mekong River delta also experienced a withdrawal of labor from rice production as the labor use decreased from 96 to 55 workdays for the same period.

Excessive land fragmentation has made the Red River delta the most labor-intensive agriculture within the country. Although land productivity was high, the limited agricultural surplus exposed farmers in the delta to less incentive from market liberalization. However, improvements in the rural labor market and wages helped to dampen the inverse relationship between farm size and productivity across regions and to release excessive agricultural labor.

2.5. Livelihood strategies and differentiated benefits from agricultural support

Income diversification is a pervasive strategy in rural economies. Given low asset endowment, labor and output market imperfections, and unsecured risks, farmers resort to diversification to generate and stabilize their incomes (Barrett *et al.*, 2001). Because the choice to be a subsistence farmer depends on landholdings, smallholders are exposed to not only fewer market incentives but also less benefit from agricultural support.

A subsistence farming household generates their income through a diversified group of activities although agriculture accounts for the most part. Their participation in agricultural markets is limited as most of the agricultural output is for consumption. Another critical point in their livelihood is the dominant role of staple crops in their agricultural production. The World Bank (2007) reported 80% of a subsistence farming household income in Vietnam was generated from agriculture while the proportion of staple crop accounted for 73% of agricultural output. For mixed households, although the importance of agriculture remained the same as it did to subsistence farming one, the relative role of staple crop declined below 70% of agricultural output. Commercial farms put an emphasis on high-value crops as they made up 39% of agricultural outcomes (World Bank, 2007).

The choice to be a subsistence household or a market-entrant or market-oriented household depends on net marketable surplus, and as a consequence, on land endowments.

Purcell (2011) estimated that a four-person Vietnam household would need a minimum annual harvested area of rice of 0.15 hectares to support their minimum living expenses. With an average arable land of 0.2 hectares, a typical farming household in the Red River delta can be regarded as a subsistence unit. In the Mekong River delta, where land endowments are more generous, better production capacity results in a commercial agriculture. During the initial years of the liberalization, a small portion of farming households was subsistence-oriented. However, improvements in market condition diminished the subsistence livelihood in the delta by 2006.

Vietnam rice producers benefited from support policies as they accounted for more than 7% of their gross revenues (OECD, 2015). However, farmers with larger farming land in the South gained more than their counterparts in the North. With a net marketable output of 40% (CIEM, 2015), an average producer support of 7% resulted in a 2.8% increase in gross receipt for farmers in the Mekong River delta. With a limited farming land and a net marketable surplus of 25%, farmers in the Red River delta just benefited from a 1.75% increase in their output sales resulted by supportive agricultural policies. Given the share of crop production in total income of 80% and 25% for farming households in the Mekong and the Red River delta, respectively, the difference in marketable output results in a 2% higher total income originating from supports for farmers in the Mekong River delta, *ceteris paribus*.

2.6. Constraints to Vietnam agriculture

A bottleneck for the development of Vietnam agriculture is the smallholdings and excessive land fragmentation although the situation was more severe in the Red River delta than in the Mekong River delta. In 2001, 67% of the peasant families in the country had arable land of no more than 0.5 hectares while 26% of them had an area of no more than 0.2 hectares. Although the land distribution did not vary much in the period 2001-2011, the fragmentation became more severe in the smallest landholding groups due to household partition. The proportion of farming households with arable land less or equal to 0.2 hectares increased to 35% while the percentage of those households with farming land from 0.2 to 0.5 hectares decreased from 41% in 2001 to just 34% in 2011 (Figure 2.3, Figure 2.4).

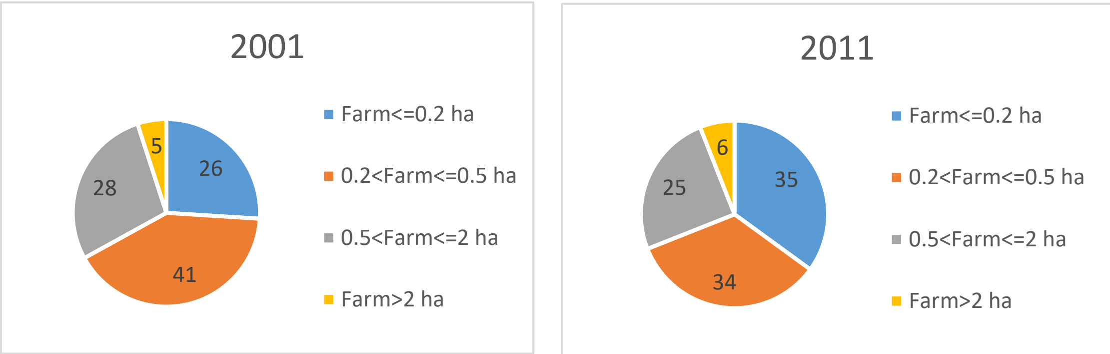

Figure 2.3. Farm size distribution in Vietnam

Source: World Bank Group (2016)

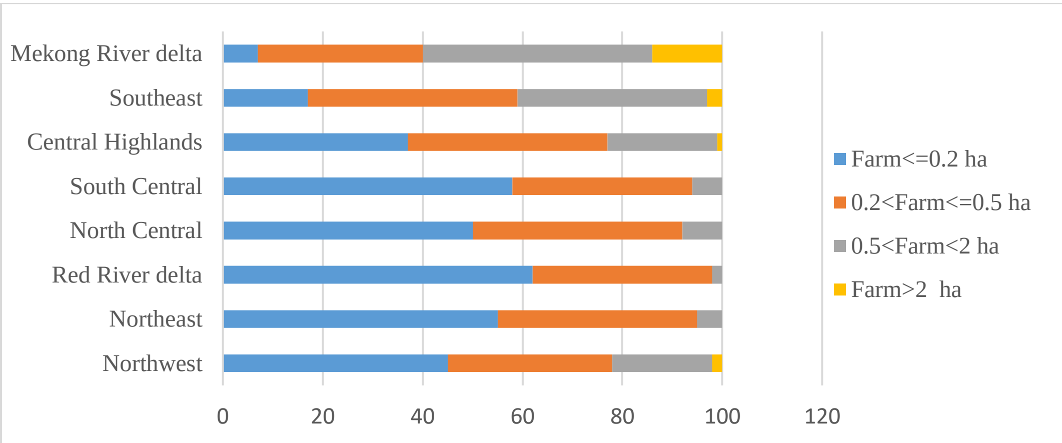

Figure 2.4. Farm size distribution across regions, 2010

Source: Tran *et al.* (2013)

The small land endowments and excessive land fragmentation not only prevents commercial agriculture but also raises difficulties in technology adoption and rationalizing production costs (Orea *et al.*, 2015; Pannell *et al.*, 2006; Moreno & Sunding, 2005). The situation is more pronounced in the North with higher population densities, relative to the South. The Red River delta is the most fragmented delta where the majority of farming households (62%) cultivated a farming area of no more than 0.2 hectares in 2010. With lower population pressure, 60% of farmers in the Mekong River delta have farming land of over

0.5 hectares while the number of those who depend on 0.2 hectares of land or less just account for 7% of total peasant families.

The sustainable success of Vietnam agriculture has been contingent on agricultural technology, and improved market and infrastructure conditions. While the easiest part of agricultural growth has been reaped through technology adoption, future development of Vietnam agriculture is facing numerous constraints. The excessive land fragmentation in Vietnam also raises difficulties in promoting a commercial and effective agriculture. Output prices are prone to unpredictable fluctuations. Prices act as profitability signal guiding farmers what to grow and how much to invest in agricultural innovation. Despite the general upward trend in global food prices, Vietnam rice prices showed a slowly increasing pattern. Official statistics from FAO show that Vietnam Producer prices reached a peak in 2009 before a declining trend until 2016. The slow increase in real output price but with considerable fluctuation across space and time is expected to negatively affect rice farmers' profits and innovation behavior.

The future development of Vietnam agriculture is expected to face additional challenges due to environmental changes. Vietnam is expected to be among the countries hardest-hit by future climate changes (Dasgupta *et al.*, 2009). Given the limited adaptation capacity, likely consequences of changing climatic conditions are believed to be serious and present threats to hunger eradication, poverty reduction, and sustainable development.

2.7. Conclusion

After the Reunification between North-South in 1975, Vietnam faced major poverty challenges. A long history under the French rule and anti-foreign wars left devastating legacies for both human well-being and economic development. The most important infrastructures in the North were destroyed. A large area of land could not be brought back to cultivation as a result of being severely poisoned by intensive pesticide spray. The whole economy was exhausted while foreign aid from the Socialist bloc to the North and American aid to the South stopped. The collectivization process contributed less economic incentives for farmers. The devaluation of domestic currency in the mid of 1980s caused escalating prices which in turn made the situation worse. Ten years after the victory over the American and Allied forces, Vietnam was among the five poorest countries with barely any prospects for the future.

The reform series initiated in 1986 opened up the economy and its agriculture to market incentives. Agricultural research and extension played an important role in agricultural productivity growth. Increasing governmental supports for the agriculture benefited farmers across regions. Several researchers have found the income gap in favor of farmers in the South. Jerez (2018) argued differentiated land endowments was a major source of economic divergence between the Red River delta and the Mekong River delta.

This chapter provided evidence of a more transformative Red River delta than prior analyses have presented. It contended that rural peasant families in the Red River delta have been working hard to maintain higher income growth, relative to their counterparts in the Mekong River delta. The key to the transformation of the Red River delta was the growth in income from wages and sidelines. Despite limited farming land, farmers in the Red River delta managed to enjoy the similar income growth from crop production. Nevertheless, small land endowments exposed farmers in the delta to less incentive from market liberalization, compared with peasants in the Mekong River delta. Albeit more pronounced in the Red River delta, improved labor markets also helped to release agricultural labor in both deltas. However, excessive land fragmentation due to high population density has made the Red River delta inherently labor-intensive. Prospects for the future are also challenging due to constraints of climate condition and market fluctuations.

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Chapter 3. Productivity impacts of hybrid rice seeds in Vietnam

Abstract: Hybrid rice varieties have been regarded as the most important measure addressing food security in developing Asian countries. The success story of hybrid rice production in China motivated the Vietnamese government to import hybrid seeds as an effort to increase rice productivity. Despite increased use of hybrid rice seeds and rising input intensity, rice productivity growth has slowed down since 2006. Using a ten-year panel of households, this paper analyzes the productivity impacts of hybrid rice seed adoption in the post-Green Revolution era. We combine Propensity Score Matching in adoption decisions with panel frontier models to control for selectivity bias. The frontier models are specified to allow for direct comparisons of the base productivity, factor productivity, and technical efficiency between hybrid and the current rice varieties. The findings show that although hybrid rice varieties affect factor productivity, they provide a lower base productivity of 0.2% indicating a deficiency of the seed technology in the period studied. The time-trend variable in the model also indicates a neutral inward shift in rice technology between 2006 and 2016. Large technical efficiency gaps exist in rice production suggesting a potential benefit of improvements in management skills with the existing technology.

Keywords: Propensity Score Matching**,** hybrid rice, selection bias, stochastic frontier, Vietnam

3.1. Introduction

The development of high-yielding rice varieties since the mid-1960s has made a vital contribution to food security and livelihoods in developing countries. The success of these varieties was characterized as a Green Revolution (Evenson & Gollin, 2003). Impact assessments have been carried across continents including Asia (Villano *et al.*, 2015; Yang *et al.*, 2007; Hossain *et al.*, 2006; Umetsu *et al.*, 2003; Rahman, 2003; Jin *et al.*, 2002; Huang & Rozelle, 1996; Rosegrant & Evenson, 1992), Africa (Abiodun Elijah *et al.*, 2017; Dontsop

Nguezet *et al.*, 2012; Ayinde *et al.*, 2009; Minten & Barrett, 2008; Barrett *et al.*, 2004). These analyses confirm the significance of high yielding varieties in improving productivity. Evenson and Gollin (2003) provided a review of the impacts of the Green Revolution from 1960 to 2000. Their work shows that high-yielding varieties contributed a 0.8% per annum increase in rice productivity. In addition, a significant part of the productivity gain in the late Green Revolution was due to the release of new varieties.

While scientists were optimistic about the Green Revolution impact during the latter half of the twentieth century, future prospects for sustaining the growth momentum in food production is still an open debate. Ruttan (2002) expressed his concern over biological technology in developing regions. Given the easiest productivity gains have been achieved, hybrid rice has been regarded as the most important technology tackling the food security concern (Food and Agriculture Organization, 2014) in populous Asia. It has been shown to provide a way out of food production stagnancy in China where more than half of the rice area is under hybrid rice with a productivity superiority of 15-20% over other inbred rice varieties (Jin *et al.*, 2002; Huang & Rozelle, 1996). In other Asian countries such as the Philippines, India, Bangladesh, and Vietnam, the production with hybrid rice has been largely dependent on imported hybrid rice seeds from China (Food and Agriculture Organization, 2014; Aldas & Hossain, 2003) due to limited biotechnology capacity. The mixed findings on the productivity impacts of hybrid rice varieties have raised a common concern over the prospect for the China's success story to be replicated outside China (Food and Agriculture Organization, 2014; Janaiah *et al.*, 2002).

Vietnam serves an interesting case for hybrid rice technology assessment due to its important role in global rice production. Rice has been the dominant crop accounting for more than 60% of the total cropping area (General Statistics Office, 2016). Vietnam is the second largest exporter of rice (Ha *et al.*, 2015; Fulton & Reynolds, 2015), with an average of 5 million tons per year between 2005 and 2015. Improved inbred varieties were the most popular cultivars as replacements for local varieties with low productivity. Since 2004, 153 hybrid rice varieties have been introduced into production, alongside other inbred high-yielding rice varieties, raising the rice area under high-yielding rice varieties up to more than 90% (Cuc *et al.*, 2008). Imported seeds from China accounted for roughly 80% of total hybrid seed demand. Despite the application of hybrid rice seeds and intensive use of fertilizers (OECD, 2015), rice productivity showed little responsiveness as the annual productivity growth continued to decrease from 2.8% between 2000-2005 down to 0.8% in the period 2010-2016. Little is known about the impacts of these hybrid seeds in Vietnam while significant funding has been allocated to imported varieties for production as an effort to increase food supply for the growing demand, both domestically and internationally.

This paper addresses the question whether hybrid rice varieties help uplift rice productivity in Vietnam. Assessing the superiority of a technology over another is complicated due to selection bias resulting from observables and unobservables (Greene, 2010; Greene, 2008; Heckman & Navarro-Lozano, 2004). Farmers who are productive with the new technology are likely to be productive with the old technology because they have higher levels of education, better information, or unobserved factors that positively affect productivity (Barrett *et al.*, 2004). The failure to address selectivity bias in previous hybrid rice assessments (Azad & Rahman, 2017; Mustafi & Hossain, 2008; Hossain *et al.*, 2006; Jin *et al.*, 2002; Huang & Rozelle, 1996) might have led to overstatements of return to hybrid rice seeds.

This work builds on the cross-sectional analysis by Villano *et al.* (2015) who evaluated the impacts of certified seeds on productivity and technical efficiency in the Philippines's rice sector. Villano *et al.* (2015) combined Propensity Score Matching (PSM) with a stochastic frontier model with correction for selectivity bias proposed by Greene

(2010). Although PSM does not completely eliminate biases stemming from observables, Imbens and Wooldridge (2009) argued that this method yields reasonable results. Our work, however, differs from Villano *et al.* (2015) in a number of ways. Our frontier models avoid the standard assumption of time-invariant technical efficiency associated with cross-sectional frontier models and other traditional panel frontier estimates. In addition, although the metafrontier model from Villano *et al.* (2015) allows direct comparisons of technical efficiency, the frontier model with correction for selectivity bias does support direct comparisons of the base productivity and factor productivity, which in many cases are our research interests. Our stochastic frontier model is specified to capture differences in the base productivity, factor productivity, and technical efficiency.

This paper makes threefold contributions to the existing literature on technology impact assessment in the rice sector. First, it is the first to examine how adoption of hybrid rice varieties affect farm productivity and technical efficiency measures using panel data. Our panel estimates on the matched sample from PSM show that the fixed-effects estimators can eliminate selection bias resulting from unobservables as long as they are time-invariant. Second, our stochastic frontier model proposes a simple way to accommodate direct comparisons of the base productivity, factor productivity, and technical efficiency between different rice seed technologies. Finally, in contrast to the common findings on positive impacts of hybrid rice seeds, this analysis documents a negative impact of hybrid rice seeds in Vietnam between 2006-2016. Large technical inefficiency gaps exist among both groups of farmers indicating potential benefits from efficiency-enhancing efforts in Vietnam rice production.

The rest of the paper is organized as follows. The next section presents the methodological framework, followed by a section describing the empirical models and data.

Section 4 discusses the results. Section 5 concludes the paper with some key findings and policy implications.

3.2. Conceptual framework

3.2.1. The stochastic frontier model for panel data

Traditional panel stochastic frontier using the fixed-effects estimators has two main shortcomings which may lead to biased estimates. Technical or cost efficiency is assumed to be time-invariant. Additionally, fixed-effects estimators force any time-invariant heterogeneity into the term that is used to capture the inefficiency (Belotti *et al.*, 2013; Greene, 2005). While the first assumption on time-invariant technical efficiency may not be relevant for long-run panel data, failing to account for time-invariant heterogeneity in stochastic frontier analysis leads to higher estimates of technical inefficiency (Belotti *et al.*, 2013).

Greene (2005) proposed a time-varying stochastic frontier model with unit-specific intercepts to rule out time-invariant heterogeneity of inefficiency. The stochastic frontier specification for output-oriented model with the dependent variable in natural log form is:

$$Y_{it} = a_i + x_{it}^{'} * \beta + v_{it} - u_{it} \tag{3.1}$$

where *Y* is output; a_i is a vector of unit-specific time-invariant heterogeneity which affects production outcome; *x* is a vector of inputs; β is a vector of unknown parameters to be estimated; *v* is a two-sided random error term; *u* is a non-negative term representing technical inefficiency; i denotes observation while t represents the time at which the observation is observed. This model allows the disentanglement of time-varying inefficiency from unit-specific time-invariant unobserved heterogeneity. Standard assumptions on the stochastic error terms are that $E(v_i) = 0$ for all i, $E(v_i v_j) = 0$ for all $i \neq j$, $E(v_i^2) = \sigma_v^2$, $E(u_i) > 0$, $E(u_i u_j) = 0$ for all $i \neq j$, and $E(u_i^2) = \sigma_u^2$. These assumptions are restrictive and can be relaxed by allowing the variances of the error terms to be a function of other variable(s).

Under the further assumption that u_{it} is half-normally distributed and there is no auto-correlation between u_{it} and u_{is}, the density function for $\varepsilon_{it} = v_{it} - u_{it}$ is:

$$f(\varepsilon_{it})=\left(\frac{2}{\sigma_{it}}\right)\phi\left(\frac{\varepsilon_{it}}{\sigma_{it}}\right)\left(1\text{-}\Phi\left(\frac{\lambda_{it}\varepsilon_{it}}{\sigma_{it}}\right)\right) \qquad \text{for } -\infty < \varepsilon_{it} < +\infty \tag{3.2}$$

where $\sigma_{it}^2 = \sigma_{vit}^2 + \sigma_{uit}^2$, $\lambda_{it} = \sigma_{uit}/\sigma_{vit}$, ϕ is the standard normal density, and Φ is the standard normal cumulative distribution function.

The output-oriented measure of individual technical efficiency in the time t is the ratio of observed output to the corresponding maximum output (when $u_{it} = 0$) (Battese & Coelli, 1995):

$$TE_{it}=\frac{E(Y_{it}/u_{it},X_{it})}{E(Y_{it}/u_{it}=0,X_{it})} = e^{-u_{it}}=1/e^{u_{it}} \tag{3.3}$$

And, the overall technical efficiency score of all observations in all periods is:

$$TE=1 - E(u) \tag{3.4}$$

To assess farm-level technical efficiency, we need to calculate the value of u_{it}. After the frontier has been fitted to the data, we can obtain an estimate of $\varepsilon_{it} = v_{it} - u_{it}$. This value is then used to disentangle the inefficiency component u_{it} by applying the conditional mean function $E(u_{it}|\varepsilon_{it})$ as presented in Jondrow *et al.* (1982):

$$E(u_{it}|\varepsilon_{it})=\frac{\sigma_{it}\lambda_{it}}{1+\lambda_{it}^2}\left[\frac{\phi(\frac{\varepsilon_{it}\lambda_{it}}{\sigma_{it}})}{1\text{-}\Phi(\frac{\varepsilon_{it}\lambda_{it}}{\sigma_{it}})} - \frac{\varepsilon_{it}\lambda_{it}}{\sigma_{it}}\right] \tag{3.5}$$

Greene (2005) termed these stochastic frontier models “True” Fixed Effects (TFE) or “True” Random Effects (TRE) according to the assumptions on the unobserved unit-heterogeneity. If the unit-specific heterogeneity, which affects production outcomes, is uncorrelated with the production process (or with other exogenous variables included in the model), a TRE model will reveal interesting facts about cross-unit heterogeneity impact. However, cross-farm heterogeneity in terms of management skills can affect the choice of rice seeds, amounts of inputs used, and productivity. Therefore, we apply a TFE model to obtain robust estimates of parameters.

3.2.2. Self – selection into new rice seed production

On-farm experiments have reported a productivity gain of 15-20% from hybrid rice seeds (Food and Agriculture Organization, 2014). However, the production with hybrid rice varieties involves higher levels of input use and a larger scale of farming for the productivity gains to be materialized. This can result in different frontiers for adopters and non-adopters of hybrid rice varieties. We are interested in measuring the productivity differences between hybrid and improved rice seeds by allowing the vector β in Equation (3.1) to differ by including a hybrid rice seed indicator (d) and its interactions with other inputs x_i. However, estimated coefficients in Equation (3.1) are subject to biases due to selectivity bias if farmers select themselves as adopters of hybrid rice. The choice of crop varieties can be associated with a broad range of factors (*w*) which can be modeled as follows:

$$P(d_i=1)=\partial_i * w_i + \omega_i \tag{3.6}$$

where ∂_i is a vector of parameters and ω_i is a random error. If any of the determinants of variety choice also affect productivity but are not explicitly included in Equation (3.1), the new seed indicator in Equation (3.1) is correlated with the error term of the frontier function. In this case, estimated parameters of Equation (3.1) are biased.

We address selection bias in Equation (3.1) using PSM in a panel setting. This approach involves three steps as follows:

In the first step, a pooled probit model is estimated to generate the probability, or the propensity score, of being hybrid rice seed for each household using Equation (3.6).

In the second step, each household with hybrid rice production is matched to a household with other inbred varieties. There are several matching algorithms (Caliendo & Kopeinig, 2008). The nearest-neighbor matching method identifies for each household in the treated group the closest twin in the opposite technological status. The caliper matching imposes a tolerance level (also known as common support condition) on the maximum propensity score distance when the closest neighbor is far away. The kernel-based matching technique identifies the neighbor as the weighted average of households within a certain propensity score distance, with weights inversely proportional to the distance.

The third step involves the estimation of the panel frontier production function described in Equation (3.1) on the matched sample generated from PSM. PSM can control for observed heterogeneity associated with both the propensity towards adoption of hybrid rice seeds and productivity. However, there may exist other unobserved factors which are also correlated with the seed indicators and the error term in Equation (3.1). These include time-invariant heterogeneity in farmer's skills, and other time-varying unobserved factors such as changes in public extension services. The fixed-effects estimators from Equation (3.1) are expected to be free from time-invariant sources of heterogeneity which are potentially associated with adoption status and productivity. Selection on unobserved time-varying factors is not a major concern if these factors are common shocks on adopters and non-adopters of hybrid rice varieties.

3.3. Empirical models and data

Following Mayen *et al.* (2010), we adopt a stochastic frontier model which allows for direct comparisons of the base productivity and factor productivity between hybrid and inbred rice varieties. First we estimate a translog functional form of Equation (3.1) using panel data. Then we test for adequacy of a Cobb-Douglas functional form to represent our data which means the estimates for second orders of input variables jointly equal zero. The likelihood ratio test has a Chi-square value of 2.9 and is not statistically significant at the conventional level. Therefore, a Cobb-Douglas functional form for our panel data is justified. Our empirical Cobb-Douglas frontier model for panel data can be written as:

$$\ln(Y_{it})=a_i+\sum_{k=1}^{K}\beta^k*\ln(x_{it}^k)+\alpha*d_{it}+\sum_{k=1}^{K}\gamma^k*d_{it}*\ln(x_{it}^k)+\tau*t+\varepsilon_{it} \qquad (3.7)$$

where Y_{it} is the rice output of household i at time t. x_{it} is a vector of production inputs, including seed, total labor days on rice production, nitrogen fertilizer application, plant protection cost, capital cost, rice area, and irrigation coverage. d_{it} is the seed indicator capturing the effect of hybrid rice seeds on the base productivity. We also allow hybrid seeds to have effects on factor productivity by including in Equation (3.7) a set of interactions between seed indicator and other inputs. t is a time-trend variable used to capture neutral technology change rather than new seeds, fertilizers, and tractors. β^k, φ^{jk}, α, γ^k, τ are vectors of parameters to be estimated.

We estimate the following probit seed selection equation to obtain the propensity score for matching:

$$P(d_{it}=1)=\partial_0+\partial_1*H_{it}+\partial_2*F_{it}+\partial_3*Socio_{it}+\omega_{it} \qquad (3.8)$$

where *H* is a vector of household characteristics, *F* is a set of farmland characteristics, *Socio* is a set of socio-economic factors. The selection of variables explaining adoption is drawn from the adoption literature (Pannell & Zilberman, 2020; Norton & Alwang, 2020; Montes de Oca Munguia & Llewellyn, 2020; Llewellyn & Brown, 2020; Chavas & Nauges, 2020; Doss, 2006; Sunding & Zilberman, 2001; Feder & Umali, 1993; Feder *et al.*, 1985).

The analysis uses the data from the Vietnam Access to Resources Household Surveys (VARHS) 2006 – 2016. The nationally representative surveys have been conducted once every two years to collect information on aspects of income-generating activities including, but not limited to, agricultural production across regions in Vietnam. The VARHS 2006 collected information on 2,324 households randomly selected across the seven agro-ecological regions in the country. Most of these households were then re-surveyed in subsequent rounds while the sample sizes have been adjusted to population growth. After dropping out observations with missing values for variables of interest, the Data Record

Linkage method generates a balanced panel of 325 households with complete information, or a total of 1,950 year-household observations. There are 1,322 year-households reported the use of hybrid rice varieties.

Table 3.1 presents a brief definition of variables used in Equation (3.7), and PSM - Equation (3.8). Because data on seed and fertilizer application were measured in value, we deflated these input expenditures using a producer price index before converting them into quantity measures using 2010 prices. For seed use, a price of 40 and 90 thousand VND were used for inbred and hybrid seeds, respectively. The most popular fertilizer used in rice production is 46% Nitrogen. We converted household fertilizer expenses into actual nitrogen application at a ratio of 1: 2.17 and a price of 5.52 thousand VND per kilo. Table 3.2 presents the main statistics and statistical significance of tests on equality of means for variables between the two groups of farmers. The unmatched sample shows significant differences between adopters and non-adopters in a broad range of factors. Households with hybrid seeds have higher levels of general education but with lower total income. The scale of rice farming is different between adopters and non-adopters of hybrid rice seeds. While an average adopter farms a rice area of more than 8,000 square meters, a non-adopter farms an area double that size. Accordingly, the average rice output of an adopter is half of a non-adopter (more than 4,500 kg versus 9,100 kg). However, the amount of inputs used does not vary proportionally to rice area indicating a potentially factor-biased technology, or excess input use by hybrid rice farmers. The amount of workdays do not vary substantially across the two groups with different average rice farming scales. Fertilizer application of an adopter is about 92kg, nearly two-thirds of a non-adopter whose rice cultivated area doubles. Although irrigation conditions are not significantly different between adopters and non-adopters (81.4% versus 85.2%), differences in irrigation conditions across households account for the large range of variations within each group (33% and 31.5%, respectively).

Table 3.1. Variable definition

	Variable	Measurement
1. Probit seed selection		
Dependent variable	Seed_indicator	The choice of rice seeds (binary, =1 for hybrid rice seeds, 0 otherwise)
Independent variables:		
Household characteristics	hh_size	Number of household members (persons)
	head_sex	Gender of household head (binary, =1 for male, 0 otherwise)
	head_edu	Formal education of household head (years)
	head_age	Age of household head (years)
	Income	Total income of household (Million VND, 2010 prices)
Farmland characteristics	no_plots	Number of separate farmland parcels (parcels)
	farm_size	Total farmland area (1,000m^2)
	Tenure	Land tenure (% of farmland owned by household)
	Irrigation	Irrigation condition (% of farmland irrigated)
	Disaster	Number of occasions the farmland experienced extreme weather events such as typhoons and droughts in the last two years (times)
Socio-economic characteristics	distance_input_supplier	Distance from household to the nearest input supplier (km)
	extension_contact	Number of extension contacts during the last year (times)
	market_share	Proportion of rice production sold (%)
	Credit	Formal credit access (binary, =1 if household resorted to formal loan)
	Agricultural_wage	Average agricultural wage in the area (1000VND/workday, 2010 prices)
2. Stochastic frontier model		
Dependent variable	rice_output	Total rice output (kg)
Independent variables:	Seed	Total seed amount (kg)
	Labour	Total workdays on rice (days, both family and hired labour)
	Fertilizer	Total nitrogen fertilizer application (kg)
	capital_cost	Other capital cost (1000VND, 2010 prices)
	Rice_area	Total rice area cultivated (1000 m^2)
	Protection_cost	Pesticide and herbicide cost (1000VND, 2010 prices)
	Irrigation	Percentage of farmland irrigated (%)

Table 3.2. Data description

	Unmatched sample				Matched sample			
	Non-adopters (N=638)		Adopters (N=1,312)		Non-adopters (N=638)		Adopters (N=638)	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
1. Selection Model								
hh_size	4.62	1.47	4.52	1.57	4.62	1.47	4.64	1.67
head_sex	0.82	0.38	0.85*	0.36	0.82	0.38	0.82	0.39
head_edu	6.17	3.42	6.81***	3.25	6.17	3.42	6.31	3.33
head_age	51.16	12.38	51.67	11.80	51.16	12.38	50.68	11.99
Income	42.56	67.16	34.97***	38.03	42.56	67.16	40.67	48.52
no_plots	4.60	2.90	5.58***	3.02	4.60	2.90	4.30	2.39
farm_size	13.03	32.71	7.31***	16.79	13.03	32.71	9.17***	18.94
tenure	0.74	0.39	0.75	0.39	0.74	0.39	0.69**	0.42
irrigation	85.00	32.00	81.00**	33.00	85.00	32.00	87.00	29.00
distance_input_supplier	20.37	33.90	6.82***	21.31	20.37	33.90	10.72***	22.43
extension_contact	1.52	2.43	1.54	2.15	1.52	2.43	1.37	2.04
market_share	0.45	0.38	0.26***	0.31	0.45	0.38	0.44	0.33
credit	0.63	0.48	0.59*	0.49	0.63	0.48	0.61	0.49
disaster	1.04	2.16	1.13	2.14	1.04	2.16	0.89	1.80
Agricultural_wage	61.98	20.51	58.43***	20.97	61.98	20.51	64.56**	21.64
2. Frontier Model								
rice_output	9151.06	21619.43	4552.92***	15159.12	9151.06	21619.43	7746.53	21252.83
Seed	89.55	196.30	33.85***	114.81	89.55	196.30	56.75***	160.82
Labour	113.76	101.09	104.52**	88.91	113.76	101.09	118.21	97.93
Fertilizer	140.25	332.70	92.27**	355.14	140.25	332.70	161.77	499.36
capital_cost	11968.20	24281.22	8575.08**	35572.76	11968.20	24281.22	14341.52	50278.70
Rice_area	16.06	33.24	8.40***	23.24	16.06	33.24	13.32	31.91
Protection_cost	7065.92	24584.60	4591.77**	26373.21	7065.92	24584.60	8859.55	37352.58
Irrigation	85.00	32.00	81.00**	33.00	85.00	32.00	87.00	29.00

**** p<0.01, ** p<0.05, * p<0.1 (sample t test for differences between adopters and non-adopters)*

There are also significant differences in socio-economic factors between adopters and non-adopters of hybrid rice seeds. Non-adopters have less access to suppliers of hybrid rice seeds as the average distance is further than for adopters. This difference may lead to higher interaction costs and weaker information about the hybrid seeds. It is also interesting to note that non-adopters tend to be more market-oriented as the proportion of marketed rice is higher for non-adopters.

Once we have estimated Equation (3.8), the propensity score was generated for the matching. We consider the single-nearest neighbor matching as this matching algorithm is expected to produce the smallest bias (Caliendo & Kopeinig, 2008). Each adopter of hybrid seeds was matched to a non-adopter with the nearest propensity score. Because the number of adopters is larger than for non-adopters (1,312 versus 638), we allow matching with replacement. In this case, one non-adopter can be used more than once as a match. By doing so, we can avoid bad matches associated with matching without replacement when adopters with high propensity are matched to non-adopters with low propensity.

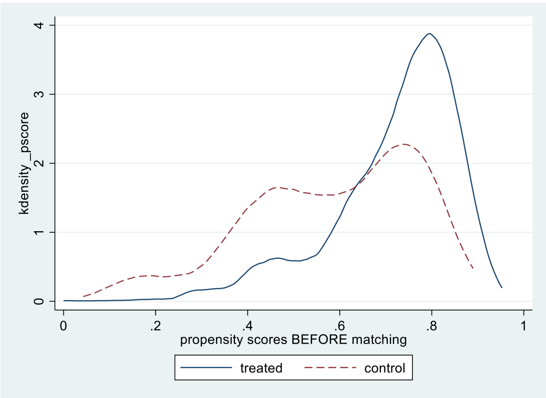

Figure 1.a

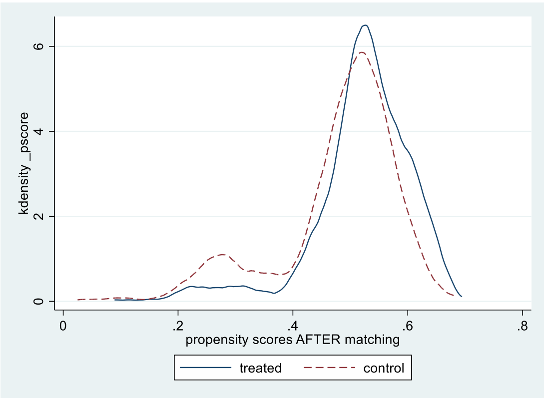

Figure 1.b

Figure 3.1. Propensity toward hybrid riceseed adoption

The matching procedure generates a total of 638 pairs of households with different adoption status. We also conducted t-tests on the matched sample to test for the balance of the sub-sample generated from PSM. Table 3.2 shows that most of the differences between adopters and non-adopters are eliminated after PSM. Figure 3.1.a depicts the differences in the propensity towards hybrid rice seed selection before PSM between the two groups. These differences contracted after PSM. Figure 3.1.b shows the similarity in the propensity score of the two groups in the matched sample. There are 35 households that appear once in the panel after PSM. Therefore, the estimation of Equation (3.7) was performed on 1,241 year-observations. The distribution of variables does not vary significantly after a small reduction in sample size. The section to follow discusses the results of the factors associated with the adoption of hybrid rice seeds and the frontier production estimates.

3.4. Estimation results

3.4.1. Propensity Score Matching analysis

The starting point of this analysis was potential selectivity bias in our productivity impact assessment. First we checked whether selection on observables is a source of bias in Equation (3.7). The probit estimates for rice seed selection using Equation (3.8) are reported in Table 3.3. The McFadden Pseudo R-squared is estimated at 0.108. Seventy-two percent of the sample is predicted accurately. The Chi-square test statistic is 266.23 and statistically significant at 1% level indicating the joint significance of the sample selection variables. In general, the probit estimates confirm the significance of the differences in variables between the two unmatched groups of farmers illustrated in Table 3.2.

The literature on agricultural technology adoption (Rajendran *et al.*, 2016; Pannell *et al.*, 2006), and in the rice sector (Mariano *et al.*, 2012) emphasizes the importance of household and farmland characteristics in predicting adoption. Our probit seed selection model confirms the statistical significance of education in explaining adoption behaviour. Farmers with higher formal education are shown to have higher propensity towards hybrid rice. Experienced farmers tend to choose hybrid rice varieties although the estimated coefficient for age is not statistically different from zero. It is interesting to note that market-oriented farmers tend to eschew adoption as the estimated coefficient for market-participation is negative and statistically significant (-0.73). While the output prices are roughly 4% lower for new rice varieties, the less marketability of new rice varieties due to perceived lower quality in terms of broken rate and fragrance (Food and Agriculture Organization, 2014; Hossain *et al.*, 2003; Janaiah *et al.*, 2002) induces market-oriented rice farmers to maintain production with inbred varieties.

Table 3.3. Selection Equation

Variables	Coefficient	Std.error
hh_size	-0.04	0.02
head_sex	0.11	0.10
head_edu	0.03***	0.01
head_age	0.01	0.00
D_income_new	-0.00	0.00
market_participation	-0.73***	0.12
no_plots	0.06***	0.01
farm_size	-0.00	0.00
tenure	0.06	0.08
irrigation	-0.01	0.11
distance_input_supplier	-0.01***	0.00
extension_contact	0.01	0.02
credit	-0.06	0.07
disaster	-0.02	0.02
agricultural_wage	-0.01***	0.00
Constant	0.62**	0.27
Observations	1,950	

**** p<0.01, ** p<0.05, * p<0.1*
(reported standard errors are clustered at household level to account for potential correlation in household decisions over time)

This analysis shows no size-biases in the adoption of hybrid rice seeds as they are a lumpy technology that is easy to adopt on a small scale with minimal start-up cost and no fixed investment. This finding echoes the work by Alauddin and Tisdell (1986) which finds no real impacts of farm size and tenure on the adoption of modern rice varieties in Bangladesh. However, land fragmentation is associated with a higher propensity towards new rice seeds as the number of farmland plots is positively associated with adoption. This finding is also compatible with the data description that shows the statistical difference in this variable between the two groups of farmers in Table 3.2.

Differences in local conditions are found to have effects on rice seed selection. The likelihood of hybrid rice variety adoption decreases in response to the travel distance to input suppliers due to increased transaction costs and weaker information flows. Although credit availability, extension services, and farmers' experience with past weather fluctuations do not show statistical significance, increases in agricultural wages are associated with lower probabilities that hybrid seeds are chosen. As illustrated in Table 3.2, the production with hybrid rice varieties requires more labor which is associated with high opportunity cost for family members. The sub-section to follow presents the frontier production functions using Equation (3.7) using the TFE estimators.

3.4.2. Frontier production function estimates

The estimation of the frontier on the matched sample is expected to mitigate potential biases due to self-selection on observables. To demonstrate how the fixed-effects estimators help eliminate selection on unobservables in the matched panel we estimated different frontier models with correction for selectivity bias suggested by Wooldridge (2015). First, we treated the data as if they were cross sections and estimate the Cobb-Douglas frontier function. Next, we estimated the Cobb-Douglas frontier model using TFE estimators. Then we conducted a Durbin-Wu-Hausman test on the endogeneity of the seed indicator in the frontiers. For the cross-sectional model the resulting Chi-squared statistic is 3.97 and statistically significant indicating that selection on unobserbable is a real concern. Farmers who select themselves as adopters of hybrid rice seeds may have better management skills. Changes in public extension services towards rice production may affect both adoption behaviours and productivity. In the latter model where panel methods was applied, the resulting Chi-squared statistic is 1.84 (p-value = 0.1750). Therefore, our TFE estimators are free from selection on farmers' ability as it is time-invariant. In addition, changes in extension services are no more a source of bias because they are uniform across adopters and non-adopters of hybrid rice.

Table 3.4 presents the estimates of three different frontiers under different assumptions on selectivity and rice seed technology.

Model (1) was estimated on the unmatched sample using the TFE estimators. Because the TFE estimators are shown to be free from selection on unobservables, this model ignore selection on unobservables.

Model (2) on the matched sample allows for self-selection on both observables and unobservables using the TFE estimators, and allows rice seed technologies to differ between adopters and non-adopters. This is the model of our interest.

Model (3) on the matched sample allows for self-selection on both observables and unobservables. However, this model assumes homogenous rice seed technology between adopters and non-adopters.

Although the TFE estimators from Model (1) are expected to be free from selection on time-invariant unobservables such as farmers' ability, the Durbin-Wu-Hausman test failed to reject the null hypothesis of exogeneity of the seed indicator due to selection on observables. Comparing Models (1) and (2) gives a sense of selectivity bias. Although the sign of most coefficients remains consistent between the two models, the larger magnitude of most input variables in Model (1) indicating overstatements of factor productivity when selection on observables is not taken into account. Our PSM analysis shows self-selection of educated farmers into new rice varieties. The estimated coefficient for labor is higher in Model (1) as a result of self-selection on education. Model (1) reports no significant differences in the productivity base between hybrid and inbred rice seeds. When selection on observables has been taken into account, hybrid rice seeds are shown to provide lower productivity potential compared with the current improved inbred rice seeds.

Table 3.4. Stochastic frontier production functions under different hypotheses

		Unmatched sample	Matched sample	
		(1) No selection on observables	(2) Heterogenous rice seed technologies	(3) Homogenous rice seed technology
	Variables			
Frontier	Ln seed	0.03	-0.10	0.07***
	Ln labour	0.20***	0.17***	0.22***
	Ln fertilizers	0.02***	0.01***	0.01***
	Ln protection	0.02	-0.08	0.02
	Ln capital	0.09	0.23**	0.06***
	Ln rice_area	0.30***	0.20***	0.38***
	Ln irrigation	-0.04	0.03	-0.01
	t	-0.03***	-0.01	-0.02***
	New seed_indicator	-0.03	-0.19***	
	New seed_indicator * Ln seed	0.15	0.25***	
	New seed_indicator * Ln labour	0.03	0.10	
	New seed_indicator * Ln fertilizers	-0.01	-0.00	
	New seed_indicator * Ln protection	-0.03	0.04	
	New seed_indicator * Ln capital	-0.06	-0.26**	
	New seed_indicator * Ln rice_area	0.15*	0.29***	
	New seed_indicator * Ln irrigation	0.07	0.07	
U_sigma	ln_rice_area	-0.02	0.04	-0.00
	Constant	-1.07***	-1.73***	-1.37***
V_sigma	ln_rice_area	0.14***	2.06***	0.97***
	Constant	-41.99***	-37.50***	-31.22***
Statistics	Log likelihood	-168.92	-64.05	-43.67
	Observations	1,950	1,241	1,241
	Number of panel_id	325	273	273

**** p<0.01, ** p<0.05, * p<0.1*

(The frontiers are clustered at household level to account for potential serial correlation resulting from unobserved time-invariant household characteristics)

The LR test for joint insignificance of the intercept shifter and interactions in Model (2) has a Chi-squared value of 11.53 and different from zero implying different rice seed technologies. Apart from higher requirements for fertilizer application, the production with hybrid rice seeds involves higher demand for labor and large rice farming scale. The failure to capture these differences in Model (3) leads to overstatements of returns to labor and rice farming scale.

We find that inputs affect rice. For households with inbred rice varieties, output elasticities to traditional inputs such as labor, fertilizers, capital cost, and rice area are positive and statistically significant. A 1% increase in labor use helps to increase rice productivity by 0.17%. The estimate for rice area has a large value of 0.2 indicating potential benefit of large scale rice farming. This result also confirms the findings of Pham *et al.* (2007), Kompas *et al.* (2012), and Diep (2013), about the positive effect of scale in Vietnam rice production.

Hossain *et al.* (2003) and Ut and Kajisa (2006) estimated approximately a 20% increase in Vietnam rice productivity due to the use of hybrid rice seeds. However, our results reveal the contrary finding. The intercept shifter is negative (-0.19) and statistically significant at indicating a lower productivity base of hybrid rice seeds over the current improved inbred rice varieties. The unconditional comparison of productivity and the failure to account for selectivity bias in their analyses would have resulted in overstatements of return to rice seed technology in Vietnam. Once selectivity bias has been controlled for, hybrid rice varieties do not improve the base productivity, compared to inbred varieties. Our finding for Vietnam is similar with the finding from Lu *et al.* (2020) for China. Nevertheless, output elasticities to traditional inputs such as amounts of seeds and labor are higher for hybrid rice seeds as the interactions between the seed indicator and those variables are positive and significant. Hybrid rice varieties require high rate of fertilizer application.

However, the estimated coefficient for the interaction term between hybrid seed and fertilizer in Model (2) is negative indicating lower factor productivity for fertilizers in hybrid rice production. This finding is also consistent with Lu *et al.* (2020) who found higher fertilizer absorption rate and partial productivity of inbred rice varieties over hybrid counterparts at a range of fertilizer application rates. The estimated coefficient for the interaction term between hybrid seed indicator and rice area has a large value of 0.29 indicating a potential benefit of large scale production with hybrid rice.

We also find evidence of an inward shift in rice technology in the period 2006-2016. The estimated coefficient of the time trend variable, t, is negative and statistically significant (-0.03). This is consistent with direct seeding in place of traditional transplanting in the Southern Central and the Northern Central which results in lower productivity although it helps to make farming less labor-intensive. The use of a time trend variable can be restrictive in the sense that it does not allow for year-specific variations in rice technology. We re-estimated the TFE model using time-fixed effects instead of a time trend variable. The estimated coefficients for all time fixed-effects are negative and statistically significant for all of the years. We failed to reject the null hypotheses that all time-fixed effects coefficients are equal. Therefore, the use of a time trend variable in our frontier model was justified.

3.4.3. Technical efficiency of rice farming

Finally, to assess managerial gaps in rice production, we measure technical efficiency levels (TE) of households against their corresponding frontiers. Table 3.5 compares estimates of technical efficiency levels from the three frontier models reported in Table 3.4. The estimated technical efficiency is slightly lower for both groups of farmers when self-selection on observables is not taken into account in Model (1). The average technical efficiency is 69.5% and is higher than an estimate of 60.6% from Diep (2013) who failed to account for neutral technology backward and selectivity bias in his analysis.

Table 3.5. Estimated technical efficiency score (%)

Model	Assumptions	Statistics	Adopters	Non-adopters	Difference in means	Total
(1)	No selectivity bias	Mean	69.9	68.8	1.1	69.5
		Std.Dev	21.1	21.2		21.1
(2)	Selectivity bias, heteogeneous rice seed technologies	Mean	72.8	71.0	1.8*	71.9
		Std.Dev	21.8	21.8		21.8
(3)	Selectivity bias, homogenous rice seed technology	Mean	69.9	73.9	-4.0***	71.9
		Std.Dev	17.6	15.4		16.6

*<0.01, ** p<0.05, * p<0.1 (t test for differences between adopters and non-adopters)*

Assuming homogeneous rice seed technology does not result in biased estimates of technical efficiency for the whole sample. The mean technical efficiency level for both groups of farmers is evaluated at 71.9% in Model (3) and is lower than the estimate of 81.6% from Khai and Yabe (2011) who failed to control for selectivity bias and lumped all the farmers in their stochastic frontier model into one group regardless of potential differences between rice technologies. However, ignoring differences in rice seed technologies results in a large technical efficiency gap of 4% in favor of non-adopters. Our TFE estimates have shown that hybrid rice seeds provide lower productivity. The failure to capture this technology inferiority underestimates managerial skills of hybrid rice farmers.

When measured against corresponding frontiers, the mean TE, corrected for selectivity bias, is estimated at 71.9%. There exist large variations in technical efficiency within each group as the standard deviations are evaluated at 21.8%. Hybrid rice farmers are 1.8 percentage point technically efficient than farmers with inbred rice varieties. This finding is similar to the findings from Villano *et al.* (2015) for the Philippines rice sector, and Abiodun Elijah *et al.* (2017) for Nigerian rice farming who found that adopters of new rice seeds are more technically efficient. An average efficiency score of 71.9% indicates a potential productivity gain of 39% ([100-71.9] / 71.9) from improvements in managerial skills for the Vietnam rice sector.

3.5. Conclusion

Stochastic frontier models estimated with panel data were employed to evaluate the impacts of hybrid rice seed technology and managerial capacity on rice productivity in Vietnam. We controlled for selectivity bias, resulting from either observables or unobservables, by combining PSM with fixed-effects estimators. While PSM mitigates selection on observables, the true fixed-effects estimators were shown to be free from unobserved heterogeneity. We adopted a stochastic frontier model that allows for direct comparisons of the base productivity and factor productivity between rice seed technologies. Model diagnostics confirmed that the production frontiers are different between hybrid and the current inbred rice varieties. The failure to account for technology differences leads to overstatements of returns to labor and rice farming scale, and lower technical efficiency for adopters of hybrid rice seeds.

Although previous impact assessments have shown potential yield gains from hybrid rice seeds, this analysis showed that hybrid varieties did not improve Vietnam rice productivity between 2006-2016. These seeds have been mostly imported from China and tested before commercial production. The lower base productivity of hybrid seeds may reflect either a drawback of the government's seed testing system or the lack of adaptability of the imported hybrid seeds to the farming conditions across regions, or both. The results also suggest an inward neutral technology shift due to the replacement of traditional transplanting. Although technical efficiency measure is higher for adopters of hybrid rice varieties due to higher managerial capacity, the average technical efficiency of Vietnam rice farming is still low and with large variations. An estimate of technical efficiency score of 71.9% suggests a 39% yield gap yet to be materialized. Therefore, improvements in extension services can be important to uplift Vietnam rice productivity.

Although our TFE estimates are expected to be free from heterogeneity, a limitation is identified. Using the household survey data, we could not distinguish between a full adopter and a partial adopter who adopted hybrid rice seeds on a fraction of their farming land. Instead, we defined a household who reported the use of hybrid rice seeds as an adopter. Our estimates are, therefore, still prone to potential biases in an unknown direction if partial adopters were included in the sample. Each farmer may have different plots with different cultivars. Future research could use plot-level data for better causal inferences because it is easier for the farmer to report plot-specific rice seeds. In addition, using plot-level panel data also helps control for unobserved heterogeneity in farming land characteristics which can be a source of biased estimates.

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Chapter 4. Measuring the impact of climate change on agriculture in Vietnam: A panel Ricardian analysis

Abstract: This paper investigates the economic impacts of changes in climate conditions on Vietnamese agriculture. We apply the two-step Hsiao method to a ten-year panel of household data which focuses on the production of 20 crops across seven regions in Vietnam. This study allows for variable market feedbacks across regions that grow different selections of crops. In this way, our paper differs from most panel Ricardian analyses which assume uniform market shocks on households. Our analysis also includes climate interactions to allow the effects of temperatures to be dependent on the levels of rainfall. Panel evidence from the Ricardian model suggests heterogeneous climate impacts across seasons and regions. Rising seasonal temperatures are associated with production losses to most regions, with spring temperatures being the exception. Increases in summer precipitation are valuable to mitigate the negative effects of rising temperatures. Changes in climate normals should not be the focus of policy makers since the simulation indicates marginal losses to agricultural productivity, both in the short term and the long term. Regions with cool climates are likely to be most affected by the projected climate change.

Keywords: Climate change, climate interactions, two-step Hsiao method, Ricardian model, Vietnam

4.1. Introduction

Vietnam represents an interesting case for assessing the impact of climate change. The country is characterized by highly heterogeneous climate conditions, and researchers expect Vietnam to be among the countries hit hardest by climate change (Dasgupta *et al.*, 2009). The long narrow shape of the country and its diverse typological conditions has resulted in seven climate regions where different selections of crops are grown. A report by the Ministry of Natural Resources and Environment (MONRE, 2009) indicates changes in climate patterns are not uniform. The report predicts that temperatures across the country will increase faster in autumn and winter. The northern region of the country will experience a shortage of rainfall in spring, and the southern region will suffer from lower precipitation during winter and spring. Researchers believe the likely consequences of changing climate conditions are serious and threaten hunger eradication, poverty reduction, and sustainable development (Trinh, 2018; Dasgupta *et al.*, 2009). Therefore, assessing the impact of climate change in Vietnam is important for adaptation policy.

Although the literature on climate impact is vast, little is known about how Vietnam agriculture will be affected. The simulation by Trinh (2018) presents significant losses due to non-marginal changes in long-term climate normals. Unfortunately, the estimated impacts of climate on Vietnam agriculture are prone to several sources of bias, which could limit the insights. First, although the model allows market shocks to have effects on agriculture, Trinh hypothesized price effects to be homogeneous across regions. Given the high heterogeneity in crop choice across regions, not allowing for heterogeneous price feedbacks across regions leads to biased estimates. Second, the assumption of additive separability of temperature and precipitation effects is misleading (Fezzi & Bateman, 2015), such that the estimated temperature effects also include the confounding effects of rainfall.

This Ricardian analysis for Vietnam uses a ten-year panel of household data on production of 20 crops across seven regions. We extract climatic and geographic data with high resolution to match the location of households. We test for stability of climate effects to justify the use of time-mean residuals in a two-step Hsiao method developed by Massetti and Mendelsohn (2011). In contrast to previous analysis assuming uniform market shocks, our analysis allows variable market feedbacks on regions with different selections of crops. In line with plant physiology (Morison, 1996; Monteith, 1977), our Ricardian analysis allows the relationship between temperature and precipitation to be mutually dependent.

Our findings show that while assuming uniform effects of exogenous market feedbacks produces marginal biases, the consequences of omitting climate interactions are severe when estimating climate impacts. Vietnam agriculture is shown to be more sensitive to changes in temperature than precipitation. Rising seasonal temperatures are associated with losses in most regions. Rising precipitation is beneficial in hot summers. Our simulation of climate impacts indicates marginal losses to agricultural productivity, with net losses ranging from 0.02% to 2.6% between 2030 and 2100. Regions with current cool climates, such as the Central Highlands and the Northwest, are expected to be affected the most.

4.2. Literature review

Agriculture is arguably the sector most affected by climate change as it is directly exposed to climate elements (Rosenzweig *et al.*, 2014). The projected impacts are severe for developing countries where agriculture directly supports the livelihood of a large proportion of the population and they have limited adaptive capacity. Estimated climate impacts on agricultural productivity are, however, subject to uncertainty, even for the same region under similar scenarios of global warming. For instance, Schlenker and Roberts (2009) projected large decreases in crop yields for U.S crops while Deschênes and Greenstone (2012) estimated small losses in agricultural profits. Deschênes and Greenstone (2012) attributed this difference in estimated impacts to the difference in the output measured, contending the important role of adaptation in mitigating climate impacts.

There have been two main approaches to assessing climate impacts on agriculture: the agroeconomic approach, and the Ricardian (hedonic) climate models. Agroeconomic analyses controls for factors associated with crop yields such that researchers can ideally isolate the effects of climate on crop growth and yield. Ewert *et al.* (2014) and Antle and Stöckle (2017) presented in-depth reviews of this approach. The main argument regarding this approach is that this method does not allow for actual adaptation taken by farmers to be measured in its outcome. The literature on climate change adaptation shows that farmers around the world have adopted different adaptation strategies. These include short-term climate-smart agriculture practices such as changes in sowing date, input mix, crop rotation, crop diversification and improving irrigation efficiency (Shahzad & Abdulai, 2021; Abdulai, 2018; Mall *et al.*, 2004; Bradshaw *et al.*, 2004). Long-term adaptations can be achieved by crop substitution (Rezaei *et al.*, 2015; Seo & Mendelsohn, 2008), or bundling agricultural technologies (Fleischer *et al.*, 2011). Therefore, the agroeconomic approach tends to overstate negative impacts (Blanc & Reilly, 2017). Mendelsohn *et al.* (1994) termed this as the *"dumb farmer scenario"*. In addition, the use of projections from this approach is limited due to the fact that the controlled variables used in agroeconomic analyses do not represent the diverse conditions of agricultural production.

The Ricardian model uses statistical tools to estimate relationships between climate and agricultural productivity. The model was first developed by Mendelsohn *et al.* (1994) based on a basic assumption that in a competitive market, land values reflect net productivity. Within this approach, adaptations are embedded in the information collected regarding farmers' behaviour (Adams, 1999), which is the main difference between this approach and the agroeconomic models. Assuming a farmer is looking to maximize income from his farm given the exogenous variables that are beyond his control, the farmer would choose a different crop or different inputs if the exogenous variables change. Looking across an array of climate conditions, there would be different crops chosen in each climate and different inputs applied (Mendelsohn & Massetti, 2017). Therefore, the profit-maximizing outcomes that the Ricardian model estimates incorporate long-term adaptation taken by farmers.

The Ricardian model has been applied to quantify economic impacts of climate change in a large number of countries across continents (see Mendelsohn and Massetti (2017) for more details about these analyses). Most of these studies estimate relationships between climate and agricultural productivity using cross-sectional data. The potentially omitted variable problem is a well-known issue associated with cross-sectional analyses (Blanc & Reilly, 2017; Fezzi & Bateman, 2015). Panel Ricardian models allow the use of location fixed-effects and time fixed-effects to account for potential omitted variables associated with unobserved time-invariant factors and common shocks, respectively. Another advantage of panel Ricardian models is the ability to test for the stability of climate effects over time for climate impact simulation. The standard assumption underpinning climate impact simulation is that climate is the only variable that changes over time. This is a restrictive assumption that assumes no future changes in agricultural technology that affects either agricultural productivity or adaptation capacity. Therefore, the estimated negative impacts should be regarded as the upper bound of climate impacts. However, this enables researchers to detect the likely changes in agricultural income that are attributable to climate change.

Panel Ricardian analyses, including Trinh (2018), Fezzi and Bateman (2015), Massetti and Mendelsohn (2011), Schlenker and Roberts (2009), and Deschenes and Greenstone (2007) detect the likely impacts of climate change against the backdrop of possible changes in global agricultural markets by the inclusion of time fixed-effects. The underlying assumption made by this approach is that the time fixed effects capture the common shocks exogenous to climate. The estimated climate impacts are still subject to potential biases if time fixed-effects capture any confounding effects of climate through climate-induced price change.

Ignoring interactions between climate phenomena can result in biased estimates of climate variables, however few Ricardian analyses address this. Monteith (1977) and Morison (1996), among others, have shown the significance of interactions between temperature and precipitation on crop growth. Surprisingly, most Ricardian analyses do not document such interaction but rather assume the impact of temperature and precipitation to be additively separable. Fezzi and Bateman (2015), Wang *et al.* (2009), and Schlenker and Roberts (2009) documented significant interactions between climates indicating potential bias in Ricardian analyses which assume the additive separability of climate phenomena.

We use the Ricardian model to measure the long-term impacts of climate change on Vietnam agriculture using a household-level panel over a period of ten years. The panel evidence suggests constant climate effects in the period studied justifying the robustness of estimated climate impacts to time-varying confounders. In contrast to previous panel Ricardian analyses assuming uniform effects on households of external changes, we allow these changes to have different effects on households in different regions. This analysis also relaxes the assumption on the additive separability of temperature and precipitation to avoid confounding effect of rising temperatures. We show in this paper that while the likely biases resulted from assuming uniform changes in external conditions are negligible, the consequences of assuming the additive separability of climates are severe when estimating climate impacts for Vietnam.

4.3. Research methodology

4.3.1. The Ricardian approach to valuing economic impact of climate change

The basic hypothesis of the climate impact assessment is that climate shifts the production function for crops. The intuition of the Ricardian model is as follows: if future climate conditions in location *A* were analogous to the current climate in location *B*, then the future behaviour of farmers in location *A* would resemble the current behaviour of farmers in location *B*, *ceteris paribus*. Therefore, information on agricultural production from cross-sections includes the implicit value of climate change. The Ricardian model assumes the farmer is always looking to maximize production income, subject to a set of exogenous conditions of his or her farm. This approach estimates the overall value of each driving factor by specifying the hedonic, reduced form model:

$$Max\ \pi = P_i Q_i(K_i, E_i) - TC_i(Q_i, W, E) \tag{4.1}$$

Where л is net crop income which is the difference between revenue (PQ) and cost (TC) per unit of farmland. P_i is the market price of crop i, Q_i is the production function of crop i, K_i is a vector of production inputs other than land, E_i is a vector of exogenous environmental factors such as climate and geographic conditions. The relationship between climate and production function is expected to be quadratic (Körner, 2006; Criddle *et al.*, 1997) such that the Ricardian model includes square terms of climate variables. Because the dependent variable is net crop income the Ricardian model takes into account adjustment cost pertaining to adaptation in terms of crop switching.

The Ricardian model defined by Equation (4.1) is a locus of most profitable crops. It is estimated across crops and inputs under different climate conditions (Wang *et al.*, 2009). Under the assumption of full adaptation given climate, net crop income or land value has attained the long-run equilibrium that contains information on the economic impact of climate change.

For a simpler illustration, we group independent variables into: a vector of time-varying variables X, a vector of time-invariant control variables Z, and a vector of climate variables C which are long-term averages of weather (Romm, 2018) and their square terms. When data are available for different years, one can use the repeated cross-sections to estimate the following Ricardian model in any year for which data are available:

$$V_{it} = X_{it}\beta_t + Z_i\gamma_t + C_i\varphi_t + u_{it} \tag{4.2}$$

This is equivalent to estimating a pooled Ricardian model with a set of time dummies and their interactions with climate variables. In the above equation, the estimated coefficients are allowed to vary over time. Climate change is a long-term trend. Different estimates of climate impact for different years seem not to be relevant (Massetti &

Mendelsohn, 2011). Therefore, the correctly specified Ricardian model using repeated cross-sections is:

$$V_{it} = X_{it}\beta + Z_i\gamma + C_i\varphi + u_{it} \tag{4.3}$$

Because the Ricardian model measures long-run impacts of climate, a single-stage fixed-effects method is not appropriate since there is no variation in climate variables. Therefore, the Ricardian model for panel data can be estimated in two ways. One is to pool the entire data set to estimate a single stage using the above equation. The second way is to apply the Hsiao two-step method developed by Massetti and Mendelsohn (2011). Researchers prefer the Hsiao method because the fixed-effects estimates of time-varying variables are robust to omitted (time-invariant) variables at the household level (Blanc & Schlenker, 2017). The details of the Hsiao two-step method are as follows:

4.3.2. The Two-stage Hsiao method for the panel Ricardian model

In the first step, net crop income or land value is regressed on time-varying variables using a fixed-effects method:

$$V_{it} = X_{it}\beta + \varepsilon_{it} \tag{4.4}$$

where ε_{it} is the resulting error term.

In the second step, the time-mean residuals (simple residuals plus fixed effects) obtained from the first step are regressed upon climate and other time-invariant controls:

$$\overline{V_i} - \overline{X_i}\hat{\beta} = Z_i\gamma + C_i\varphi + \overline{u_i} \tag{4.5}$$

While the estimated coefficients for time-varying variables in Equation (4.4) are robust to omitted time-invariant factors, the estimated climate impacts using Equation (4.5) are still prone to unobserved heterogeneity. Differences across regions in terms of soil properties and climate may lead to systematic differences in crop choice and productivity. Variations in global agricultural markets can be associated with changes in agricultural incomes. Panel Ricardian models can control for those potential omitted variable problems by using two way fixed-effects (Blanc & Reilly, 2017). The estimation of Equation (4.5) can include a set of regional dummies to account for unobserved time-invariant heterogeneity across regions. To account for potential omitted time-varying factors, one can include in their regression a set of time dummies to capture common shocks which can affect agricultural income.

4.3.3. Methodology considerations

Using two way fixed-effects can (partly) control for omitted heterogeneity when estimating climate impacts. Panel Ricardian estimates are still subject to biases from time-varying confounders if unobserved time-varying factors are associated with climate. In a long-run panel there may exist price adjustments to climate change. In this case the use of time fixed-effects are problematic because they are endogenous in the Ricardian model. A simple way to test for the stability of climate effects is to introduce to the model interactions between time dummies and climate (Massetti & Mendelsohn, 2011). The test for stability of climate impacts is simply a test on the joint insignificance of the coefficients associated with time-climate interactions. If the null hypothesis is not rejected, confounding effects of unobserved time-varying factors are not a major concern. The subsequent Ricardian model can be re-estimated without time-climate interactions and the use of time-mean residuals in the second step of Hsiao method is relevant.

Our Ricardian analysis implicitly models long-term adaptation in terms of crop choice such that farmers in different climate conditions grow different selections of crops. Agricultural commodities may react differently to market variations. Failing to address heterogeneous price change effects is therefore expected to produce biases to climate and/or other time-invariant controls in Equation (4.5). A general approach to introduce heterogeneous price feedbacks is to include a set of interactions between regional dummies and time dummies. If the test for the compound hypothesis that all coefficients associated with interactions between time and regional dummies are equal is not rejected, then the Ricardian model can be re-estimated without these interactions.

4.4. Empirical model and data

4.4.1. Empirical Ricardian model

This analysis uses a ten-year panel of farm-level data which allows us to use two way fixed-effects to better control for omitted variable problems. Following Van Passel *et al.* (2017), this analysis uses the log of net crop income as the dependent variable as it has more predictive power compared to the linear model. Some of the independent variables are also in natural logarithm form. Seasonal temperatures and rainfalls are introduced to the model to capture seasonal effects (Van Passel *et al.*, 2017). We relax the assumption of the additive separability of climate effects through the inclusion of interactions between temperature and precipitation, allowing the effects of temperature and precipitation to be mutually dependent.

We first justify the use of the two-step Hsiao method by estimating Equation (4.2) using the following pooled model:

$$lnV_{it} = X_{it}\beta + Z_i\gamma + C_i\varphi + u_{it} \tag{4.6}$$

Equation (4.6) includes a set of interactions between time dummies and climate variables. We use the Likelihood Ratio test (LR) to test for stability of climate impacts under the null hypothesis that all coefficients associated with time and climate interactions jointly equal zero. The LR test has a F-statistic of 1.52 and a p-value of 0.07. We fail to reject the null hypothesis that climate impacts are consistent over time at the 5% level. Our climate estimates are, therefore, expected to be free from time-varying confounders. The LR test also lends itself to the application of the time-mean residuals using the two-step Hsiao method described in the methodology section.

Next we estimate the first step of the Hsiao method using fixed-effect estimators:

$$lnV_{it} = X_{it}\beta + \varepsilon_{it} \tag{4.7}$$

Then, the time-mean residuals (simple residuals plus fixed effects) obtained from Equation (4.7) are regressed upon climate and other time-invariant controls:

$$\overline{lnV_\iota} - \bar{X}_\iota \hat{\beta} = Z_i \gamma + C_i \varphi + \bar{u}_\iota \tag{4.8}$$

with interactions between time dummies and climate variables being excluded.

Vietnam's long narrow shape of the country and the complex typology results in seven climate zones. The long-term adaptation taken by farmers in terms of crop choice has resulted in different crop selections across regions (Nguyen, 2017). We capture potential differentiated price effects through the inclusion of interactions between time and regional dummies. Our Ricardian model in the second step of the Hsiao method takes the following form:

$$\overline{lnV_\iota} - \bar{X}_\iota \hat{\beta} = \alpha + \delta * E + \gamma * R + \tau * D + \mu * R * D + \gamma_1 * T + \gamma_2 * T^2 + \gamma_3 * P + \gamma_4 * P^2 + \gamma_5 * T * P + \bar{u}_\iota \tag{4.9}$$

where *E* represents elevation, *R* a vector of regional dummies, *D* a vector of time dummies, *R*D* a vector of interactions between time and regional dummies used to capture heterogeneous price feedbacks across regions, *T* a vector of four seasonal temperatures, *P* a vector of four seasonal precipitations, *T*P* a vector of interactions between temperatures and precipitations, $\bar{u}_\iota$ an error term which is assumed not to be correlated with climate.

The marginal impact of seasonal temperatures on agricultural income is calculated using the following equation:

$$\frac{\partial \overline{lnV_\iota}}{\partial T} = \gamma_1 + 2 * \gamma_2 * T + \gamma_5 * P \tag{4.10}$$

In addition, the marginal impact of seasonal precipitations on agricultural income is:

$$\frac{\partial \overline{lnV_\iota}}{\partial P} = \gamma_3 + 2 * \gamma_4 * T + \gamma_5 * T \tag{4.11}$$

Because the dependent variable is in log form, the estimated marginal effects using Equations (4.10) and (4.11) are interpreted as percentage change in agricultural income due to one unit change in the corresponding climate variable. The estimation of Equation (4.9) uses area of household farmland as weights for two reasons. First, estimates of climate change from households with large crop production are more precise than from households with small production. Second, using farm size as weights can correct for heteroscedasticity (Deschenes & Greenstone, 2007) which is problematic in econometric modelling.

4.4.2. Data

This analysis uses the nationally representative survey data from the Vietnam Access to Resources Household Surveys (VARHS). These datasets contain rich information on income activities from production of 20 crops across seven regions. The Probabilistic Data Record Linkage method applied to these datasets produces a ten-year unbalanced panel of 2,340 households or 8,356 year-households. Following Wang *et al.* (2009) and Seo *et al.* (2009), this study uses net crop income per square meter as a proxy for land value in Equations (2)-(11). Household's self-consumed products are evaluated at market prices. To ensure the comparability, economic variables are converted to constant 2010 VND.

The climate data were derived from Worldclim version 2.0 (Fick & Hijmans, 2017) and have a high resolution of one square kilometer. Because we use climate data with high resolution, the matching between climate and household location results in low probability of mismatch. This study uses seasonal averages of temperature and rainfall for the period 1970-2000 based on the season classification of the Ministry of Natural Resources and Environment (MONRE, 2009) to support the identification of heterogeneous climate impacts. Climate and agricultural production may vary across altitudes (Mendelsohn *et al.*, 1994). We extract data on elevation with the same resolution using free spatial data from the DIVA-GIS website.

Rising population may create pressure to use land efficiently (Mendelsohn *et al.*, 1994). Increases in agricultural wages may be associated with higher opportunity cost for family labor and higher hired labor costs. The VARHS surveys on the commune level represent a rich set of data on agricultural wages. The wage data are combined with household data by applying the same Probabilistic Data Record Linkage method. Data on population density come from Vietnam Government Statistical Office. Table 4.1 presents a brief definition of the variables while Table 4.2 provides the regional averages of the data used. The data description highlights the heterogeneity of climate and socio-economic conditions which are hypothesized to have impacts on agricultural performance across regions.

Table 4. 1. Variable definition

Variable	Measurement
Dependent variable	
income_meter (in log form)	Net crop income per square meter = (total output value evaluated at market price - total cost)/farmland Thousand VND/square meter (2010 prices)
Household characteristics	
hh_size	Number of household member (person)
head_sex	Gender of household head, binary (1 = male)
head_edu	Formal schooling of household head (year)
head_age	Age of household head (year)
Farmland characteristics	
no_plots	Number of separate farmland plots
farm_size	Farm size (square meter)
irrigation	% of farmland irrigated
Socio-economic characteristics	
Extension_contact	*Number of extension contacts in the last two years (times)*
Wage	(log) Thousand VND/ workday in agriculture (communal average)
Population density	(log) Thousand persons/square kilometer
Topographic characteristics	
Elevation	Meter
Climate variables	
Winter_tem	Winter monthly temperature (Celsius degree)
Spring_tem	Spring monthly temperature (Celsius degree)
Summer_tem	Summer monthly temperature (Celsius degree)
Autumn_tem	Autumn monthly temperature (Celsius degree)
Winter_pre	Winter monthly precipitation (millimeter)
Spring_pre	Spring monthly precipitation (millimeter)
Summer_pre	Summer monthly precipitation (millimeter)
Autumn_pre	Autumn monthly precipitation (millimeter)
Regional dummies	Red River delta, Northeast, Northwest, Northern Central, Southern Central, Central Highlands (Mekong River delta as reference)
Time dummies	2008, 2010, 2012, 2014, 2016 (2006 as reference)

Table 4.2. Sample means by region

Group	Variable	Red River	Northeast	Northwest	Northern Central	Southern Central	Central Highland	South	Total
Agricultural income	Income_meter	3.67	3.78	1.75	2.30	1.69	5.35	2.81	3.12
Household characteristics	hh_size	4.31	4.09	5.42	4.27	4.23	4.88	4.34	4.53
	head_sex	0.79	0.79	0.91	0.84	0.74	0.86	0.77	0.82
	head_edu	6.95	7.34	4.25	7.44	6.03	6.42	5.29	6.25
	head_age	51.74	53.15	47.25	53.43	55.53	47.91	55.64	51.65
Farmland characteristics	no_plots	5.35	6.58	5.30	5.38	4.40	3.41	3.00	5.00
	farm_size	2,399	4,353	11,861	6,419	5,818	16,384	18,636	8,350
	Irrigation	92.00	76.00	42.00	73.00	76.00	65.00	89.00	74.00
Social-economic conditions	Extension contact	1.05	1.61	1.55	1.91	1.58	1.21	1.57	1.43
	wage	119.91	90.95	214.52	94.59	93.73	109.59	98.45	123.91
	Population_density	1,825.77	382.19	67.27	183.94	150.80	117.45	323.82	595.26
Climate conditions	Winter_tem	17.50	16.98	16.04	18.65	21.74	21.28	25.88	18.99
	Spring_tem	23.71	23.31	22.64	24.25	26.44	24.77	28.54	24.40
	Summer_tem	28.86	28.07	25.68	28.95	28.97	24.15	27.96	27.53
	Autumn_tem	24.53	24.14	22.07	24.61	25.60	22.82	27.24	24.20
	Winter_pre	20.35	26.65	22.07	32.16	112.71	20.07	18.09	33.18
	Spring_pre	103.72	105.78	117.30	67.91	45.16	110.25	84.83	95.55
	Summer_pre	287.29	276.80	351.89	167.68	111.62	210.29	206.32	249.33
	Autumn_pre	154.96	149.29	94.19	205.07	398.44	205.54	211.38	187.27
Topographics	Elevation	7.89	61.40	601.52	49.28	78.93	569.37	2.29	202.32

4.5. Estimation results

4.5.1. Hsiao estimation of step 1 – effects of time-varying factors on agricultural productivity

We used a fixed-effects method to estimate Equation (4.7). Household production can be correlated over time as the households exhibit unobserved time-constant characteristics. We take potential serial correlation in household's agricultural performance into account by clustering the errors by household. Table 4.3 presents the estimates for time-varying variables. Most of the coefficients are statistically significant at 5% indicating the relevance of most variables in explaining variations in agricultural income. Increases in population are positively associated with land use efficiency due to the pressure of lowering per capita farming area.

Table 4.3. The Hsiao estimates of step 1

	Coef.	Std. Err.
hh_size	0.054***	0.010
head_sex	-0.012	0.070
head_edu	0.010**	0.004
head_age	-0.002	0.002
no_plots	0.016***	0.006
log_farm_size	-0.497***	0.035
irrigation	0.198***	0.040
extension_contact	0.021***	0.005
wage	0.000***	0.000
log_population	0.141*	0.074
Observations		7,539
Number of panel_id		2,340

**** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at household level.*

Household size and education positively correlate with agricultural performance. There exists an inverse relationship between farm size and productivity which is consistent with the literature (Helfand & Taylor, 2020; Barrett *et al.*, 2010; Feder, 1985). A one percentage point increase in farm size is associated with roughly a 0.5% decrease in income per square meter. As expected, increases in irrigation coverage are associated with higher agricultural income. Land fragmentation in contrast, is associated with higher productivity. Our finding is contrary to the findings for South Asian countries by Niroula and Thapa (2005), and for Vietnam by Tran and Vu (2019). These analyses attribute the negative effects of land fragmentation to the disadvantages associated with higher production costs and lower production efficiency. However, land fragmentation is associated with crop diversification which is an adaptation strategy to natural and economic shocks in the Vietnam context (Nguyen *et al.*, 2017).

4.5.2. Hsiao estimation of step 2 – impacts of climate and other time-invariant controls

Previous panel Ricardian models (Trinh, 2018; Fezzi & Bateman, 2015; Massetti & Mendelsohn, 2011; Schlenker & Roberts, 2009; Deschenes & Greenstone, 2007) capture changes in global agricultural markets as common shocks to all households. However, variations in global commodity prices are not uniform (Haile *et al.*, 2016). We allow for differentiated market shocks to farmers in regions that grow different selections of crops by including a set of interactions between time and regional dummies. The estimation of step 2 of the Hsiao method also includes a set of interactions between seasonal temperatures and precipitations. Most coefficients of these interactions are significant at the conventional level. We report in Table 4.4 hypothesis tests to support our arguments before reporting the estimates of step 2 using Equation (4.9).

Table 4.4. Hypothesis testing

Null hypothesis	Variable on which its coefficient(s) is (are) tested	Value to be tested	F test value	p-value	Decision
Homogenous market shocks across regions	Interactions between time and regional dummies	Jointly equal	3.45	0.000	Reject
No climate interactions	Interactions between seasonal temperatures and precipitations	Jointly equal zero	9.52	0.000	Reject

The test results indicate heterogeneous price feedbacks across regions as a result of inherent differences in farming structures and non-uniform changes in agricultural commodity prices. The inclusion of interactions between regional and time dummies are, therefore, expected to improve the precision of regional impacts of climate. In addition, the LR test on climate interactions strongly rejects the null hypothesis on the additive separability of climate. The inclusion of climate interactions is expected to produce more accurate estimates of each climate phenomenon. Table 4.5 contrasts the estimates for climate variables across assumptions on effects of price change and climate interactions.

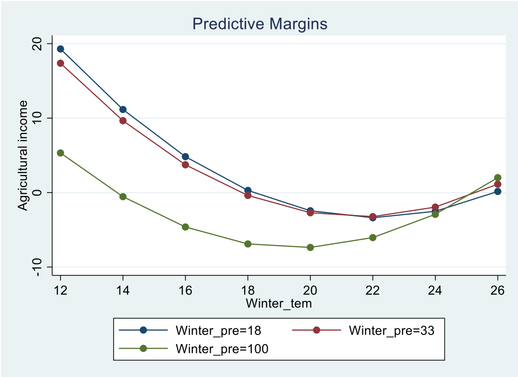
The estimated coefficients of most climate variables and their square terms are statistically significant in the three models indicating nonlinear responses of agriculture to climate. Once climate has been controlled for, farms located in higher elevations tend to be less productive as the estimated coefficients for elevation is negative (-0.002). The sign and statistical significance of variables do not change substantially across the first two models under the alternative assumptions on market shocks. However, the assumption of homogenous market shocks in Model (2) produces relatively larger estimates for most climate variables indicating potential overstatements of climate impacts due to confounding effects between external changes and regional farming systems.

We find the effects of rising temperature are dependent on the levels of rainfall in the four seasons. Figure 4.1 illustrates interactions between climate elements. Rising temperature in the winter is harmful to agriculture. The negative impact of rising winter temperature is even more severe with higher levels of rainfall (Figure 4.1.a). Spring temperatures below 24°C are harmful. Further increases in spring temperature are more beneficial as long as there is a low level of rainfall for plant pollination (Figure 4.1.b). Rising summer temperature is expected to cause losses. The likely negative impacts of a hotter summer are mitigated by a high level of rainfall of 350 mm/month (Figure 4.1.c). Agricultural income exhibits an inverse U-shape relationship with autumn temperature. A high precipitation of 350 mm/month is expected to maintain positive marginal impact of rising autumn temperature (Figure 4.1.d). These findings of beneficial impacts of precipitation in seasons with high temperatures are in line with the farm-level findings by Fezzi and Bateman (2015) for Great Britain. Ignoring climate interactions severely biases our climate impacts. Comparing Models (1) and (3) gives a sense of omitted climate interaction. The estimates for seasonal temperatures and precipitations are much smaller in magnitude in Model (3) indicating that the estimated climate impacts hide their nature due to the inseparability of temperature and precipitation.

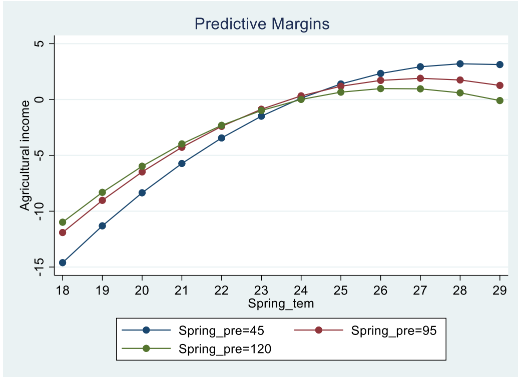
Table 4.5. Hsiao estimates of step 2

VARIABLES	(1) Heterogeneous market shocks across regions, climate interactions	(2) Homogeneous market shocks across regions, climate interactions	(3) Heterogeneous market shocks across regions, no climate interactions
Winter_tem	-10.163***	-10.242***	-4.216***
Winter_tem square	0.225***	0.229***	0.097***
Spring_tem	9.901***	9.615***	5.083**
Spring_tem square	-0.168***	-0.161***	-0.096**
Summer_tem	-10.134***	-10.932***	-6.854***
Summer_tem square	0.194***	0.209***	0.127***
Autumn_tem	23.510***	25.201***	8.918***
Autumn_tem square	-0.471***	-0.513***	-0.192***
Winter_pre	-0.261***	-0.228***	-0.032*
Winter_pre square	-0.001***	-0.001***	0.000
Spring_pre	0.235***	0.270***	-0.043*
Spring_pre square	-0.000	-0.000	0.000
Summer_pre	0.133***	0.121***	0.026***
Summer_pre square	-0.000	-0.000	-0.000**
Autumn_pre	0.057	0.023	-0.041***
Autumn_pre square	0.000***	0.000***	0.000***
Winter_tem x Winter_pre	0.014***	0.012***	
Spring_tem x Spring_pre	-0.008***	-0.010***	
Summer_tem x Summer_pre	-0.004***	-0.004***	
Autumn_tem x Autumn_pre	-0.005***	-0.003*	
Elevation	-0.002*	-0.002	-0.000
Constant	-186.041***	-189.743***	-27.634**
Time dummies	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes
Time * regional dummies	Yes	No	Yes
observations	8,356	8,356	8,356
R-squared	0.100	0.089	0.095

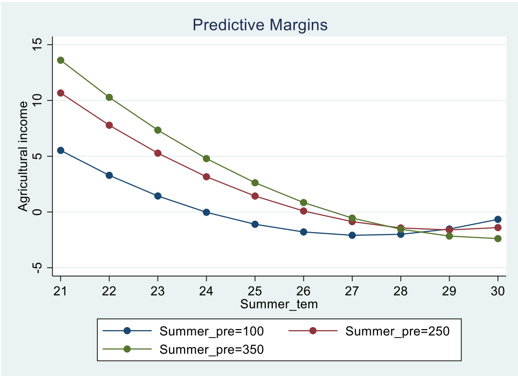
**** p<0.01, ** p<0.05, * p<0.1*



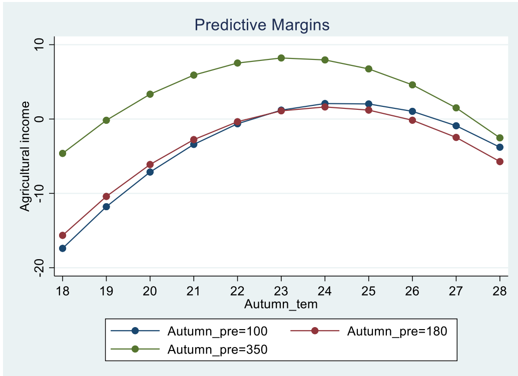
1. a



1. b



1. c



1. d

Figure 4.1. Interactions between temperatures and precipitations

The inclusion of square terms, and interactions between climate variables makes each individual coefficient in Table 4.5 no longer represent the true marginal effect of each variable. We derive the average marginal effects of seasonal climates using Equations (4.10) and (4.11) for Model (1) reported in Table 4.5. Vietnam is characterized by diverse climate conditions and topology. We are interested in how the marginal effects vary across regions in order to understand how non-marginal changes in climate conditions will likely affect agriculture. Table 4.6 summarizes the estimated marginal effects of a one-unit change in seasonal temperatures and precipitations across seven regions. We do not sum across seasons because it does not make sense to assume uniform changes in climate patterns in the whole year.

Table 4.6. Marginal effects of seasonal climates

Region	Winter_tem	Spring_tem	Summer_tem	Autumn_tem
	% change in net income per m^2 per ºC			
Red River delta	-2.005***	1.059***	-0.194	-0.341
Northeast	-2.206***	1.219***	-0.496	0.129
Northwest	-2.632***	1.305***	-1.769***	2.320***
Northern Central	-1.379***	1.058***	0.160	-0.494
Southern Central	0.899**	0.702**	0.254	-1.919***
Central Highlands	-0.251	0.567**	-1.631***	0.904
Mekong River delta	1.822***	-0.458	-0.105	-3.286***
	% change in net income per m^2 per mm/month			
	Winter_pre	Spring_pre	Summer_pre	Autumn_pre
Red River delta	-0.045***	-0.008	-0.004	-0.003
Northeast	-0.058***	-0.005	0.000	-0.002
Northwest	-0.067***	-0.006	0.007	-0.013
Northern Central	-0.039**	-0.003	0.001	0.009
Southern Central	-0.100***	-0.004	0.004	0.072***
Central Highlands	0.010	-0.023***	0.018***	0.022***
Mekong River delta	0.074**	-0.041***	0.003	0.004

**** p<0.01, ** p<0.05, * p<0.1*

Table 4.6 also indicates that Vietnam agriculture is less sensitive to precipitation than to temperature. Increases in winter precipitation are associated with losses to the whole northern region and the Southern Central with net losses ranging from 0.039% to 0.1%. More precipitation in spring in contrast, is associated with losses to the Central Highlands and the Mekong River delta. Because these two regions are the most important producers of coffee, fruit and other perennial crops, rising spring rainfall is harmful to plant pollination. Although increases in summer precipitation are beneficial, the estimated impact is significant for the Central Highland. In the autumn when precipitation is high (as shown in Table 4.2), further increases in rainfall are likely to cause losses to the northern region where annual crops are grown. The estimated impacts are positive and statistically significant for the Southern Central and the Central Highlands where irrigation coverage is relatively limited.

Rising winter temperature is likely to cause losses. As depicted in Figure 4.1.a, a 1ºC increase in winter temperature is associated with losses ranging from 0.25% to 2.6% for most regions. Figure 4.1.b indicates the optimal spring temperature of 28 ºC. Because the current spring temperature in most regions, except the Mekong River delta, is below this optimal level, a 1ºC increase in spring temperature is likely to be beneficial for most regions, with net surpluses ranging from 0.5% to 1.3%. The Northwest and the Central Highlands with cool summer climate are expected to suffer from hotter summers. The optimal autumn temperature is 24ºC, as shown in Figure 4.1.d. Because the current autumn temperature is above this level, a warmer autumn is likely to be associated with losses to the Southern Central and the Mekong River delta, with the Mekong River being the most severely affected.

4.6. Climate impact simulation

In the long-term Vietnam is expected to experience non-marginal changes in climate patterns. The expected changes in temperature and rainfall will not be uniform across seasons and across regions (MONRE, 2009). Temperature is projected to increase by 0.4°C to 3.2°C between 2030 and 2100. Autumn and winter temperatures are projected to increase faster than those in spring and summer. The Northern region will experience faster increases in seasonal temperatures. Regional and national averages of precipitation are projected to increase but with different patterns for seasons. Therefore, it is important to measure how these non-marginal changes in climate conditions will affect Vietnam agriculture so as to propose adaptation policy.

Vietnam has issued and implemented several mitigation-related policies and programs covering the main sources of greenhouse emission including energy, agriculture, land use, land use change and forestry, waste management, and industrial processes. The updated version of Vietnam Nationally Determined Contributions (NDCs) submitted in 2020 stated the goal to reduce total emission by 27% by 2030 compared to the business-as-usual scenario. Agriculture is a one of the main sources of emission accounting for 35.8% of total national emission (MONRE, 2014). However, the current NDCs indicate little contribution by Vietnam agriculture while the agricultural pathways focus mainly on crop choice, land use change, and waste management (UNFCCC, 2020). Therefore, we assume no significant changes in future technology will change the productivity of the studied crops. Rather, this simulation is an effort to measure how Vietnam agriculture is likely to be affected by the projected climate change.

The conventional approach to simulating climate change effects is using the estimated marginal effects and the predicted climate changes (Trinh (2018) , Wang *et al.* (2009), Seo *et al.* (2005), Schlenker *et al.* (2005), Mendelsohn *et al.* (1994), among others). Because the marginal effects depend on the values of independent variables (Wooldridge, 2012, p. 591), say climate, then these marginal effects do not represent precisely the relationships between agricultural income and climate conditions when future climate values are not within the observed range of values. In addition, nonlinearity in the production function and climate interactions that are not apparent in the historical range of climate data may change the relationship between the dependent variable and climates (Blanc & Reilly, 2017).

We pay special attention to the prediction of the dependent variable in logarithm form. A consistent estimator for predicting values from a regression on the log form of a dependent variable takes three steps (Wooldridge, 2012, p. 213):

First, we run the regression of log values of crop income which are time-mean residuals obtained from Equation (4.7) on explanatory variables to obtain the predicted log values of the dependent variable and residuals using Equation (4.9).

Second, the mean of the exponentiated residuals is calculated and used as the adjustment factor to scale up the exponentiated predicted log values.

Third, the original values of crop income are regressed on the exponentiated scaled-up predicted log values with no constant.

We replicate these steps for the prediction of crop income for: (1) the baseline climate under the assumption that there will be no future changes in climate conditions to obtain predicted values $\hat{y}_0$ for each household; and (2) for the years 2030, 2050, 2100 under the climate change scenarios while other control variables remain unchanged, $\hat{y}_1$. The predicted impacts of climate changes on agricultural productivity are derived by subtracting the predicted values $\hat{y}_1$ from the predicted values $\hat{y}_0$. Table 4.7 presents the estimated results while Figure 2 visualize the predicted changes in net crop income for regions in the period 2030-2100.

Table 4.7. Predicted changes in crop income under medium climate change scenario

Region	Current value (VND/m^2)	Predicted value (VND/m^2)	2030		2050		2100	
			% change	Std. Dev.	% change	Std. Dev.	% change	Std. Dev.
Red River delta	3,831	3,510	-0.029	0.608	-0.078	1.509	-0.146	3.395
Northeast	3,007	3,776	-0.105	0.185	-0.273	0.472	-0.555	0.946
Northwest	1,955	1,853	-0.498	0.834	-1.316	2.195	-2.672	4.441
Northern Central	2,449	2,343	-0.036	0.405	-0.102	1.093	-0.227	2.176
Southern Central	2,610	2,475	-0.021	0.616	-0.052	1.638	-0.108	3.394
Central Highlands	5,088	4,769	-0.088	0.126	-0.225	0.303	-0.452	0.587
South	2,970	2,485	-0.100	0.527	-0.274	1.245	-0.632	2.067
Whole country	3,169	3,081	-0.120	0.581	-0.319	1.497	-0.673	3.093

(Nation-wide impacts of climate change are averaged across regions using agricultural land as weights)

Previous Ricardian analyses present a mixed picture of climate change impacts across continents. European agriculture is more sensitive to climate change than American agriculture (Van Passel *et al.*, 2017). While Southern Europe countries are expected to be vulnerable to the projected climate change, Northern Europe is expected to benefit (Van Passel *et al.*, 2017). Maddison *et al.* (2007) showed that African countries are likely to suffer from future climate change but the estimated impacts vary by country. Ethiopia and South Africa are hardly affected with mild losses ranging from 1.3% to 3% by 2050. Our simulation for Vietnam indicates that Vietnam is likely not to be affected by future changes in climate normals, with average losses ranging from 0.1% to 0.6% between 2030 and 2100. Given the assumption of no future technology change in agriculture, the impacts might end up being even smaller if future technology is introduced into agriculture. This finding is contrary to the simulation by Trinh (2018) which presents huge losses to Vietnam agriculture. In addition to potential errors pertaining to simulation method, the overstated climate impacts by Trinh (2018) are attributable to the failure to capture climate interactions and heterogeneous seasonal and regional climates.

Figure 4.2 visualizes the distribution of changes in net agricultural income by region between 2030 and 2100. Among the regions, the Central Highlands with current cool climate is expected to be the most affected by future climate changes. In the short term, the projected climate change in 2030 is likely to cause losses of 0.5 to 1 percentage to income in the region. In the long-term when the projected increases in temperature and declines in precipitation are likely to result in 2 to 3 percentage losses in income. The Mekong River delta and the Northwest are expected to experience marginal losses of 0.5% to 1%. However, the Red River delta where irrigation covers more than 90% of the cropping area is hardly affected by future changes in climate normals.

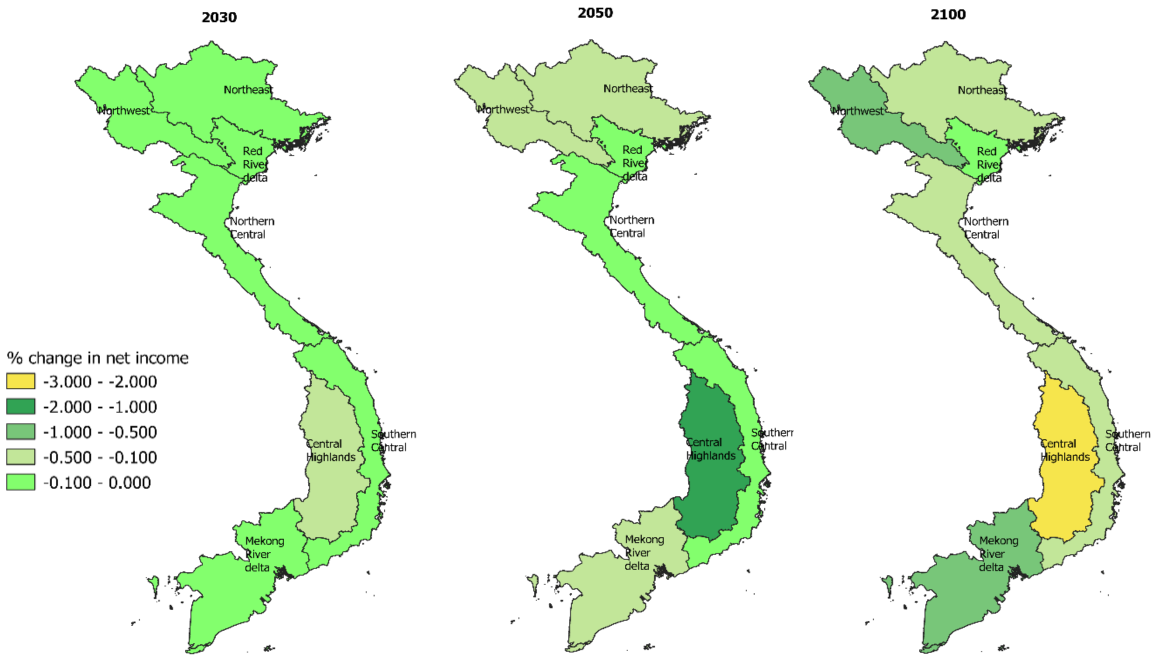


Figure 4.2. Percentage change in net income predicted by medium emission scenario

4.7. Conclusion

This panel Ricardian analysis measures the sensitivity of Vietnam agriculture to climate change using the Hsiao-two step method on a panel of ten years. We tested for potential confounding effects of unobserved time-varying factors in the model. The results indicate that our climate estimates are free from unobserved time-varying confounders. Most previous panel Ricardian analyses assumed global price changes to be common shocks to all households. However, our paper shows that market shocks have variable effects on regions growing different selections of crops. While ignoring heterogeneous price feedbacks across regions produces biases to climate estimates, the likely consequences of omitting climate interaction are even more severe.

Empirical evidence from this study suggests that farms located at higher altitudes are less productive. Rising population puts pressure on the efficiency of land use. The results confirm the inverse relationship between landholdings and agricultural productivity, which is in line with findings from Barrett *et al.* (2010) and Tran and Vu (2019). The Ricardian results highlight the nonlinear, seasonal role of changing temperature and precipitation. Increases in winter, summer, and autumn temperatures are harmful to agriculture, while the opposite is true for spring temperature. More rainfall in winter and spring is likely to reduce agricultural income, while increases in precipitation in the summer and autumn are predicted to benefit agriculture. The simulation indicates marginal regional losses ranging from 0.02% to 2.6% between 2030 and 2100. Regions with current cool climate such as the Central Highlands and the Northwest are likely to experience above average losses. The Red River delta is shown to be minimally affected in the long run. Consequently, the projected changes in long-term temperature and precipitation should not be a major concern.

Although our analysis is an advance on prior research opportunities arise for further research to progress understanding. We based the simulation of climate change impact on the hypothesis that Vietnam farming systems remain unchanged in the future. Therefore, our estimated impacts of climate change do not capture future technical changes to either crops or farming techniques. Further, although we had data on agricultural wages at the commune level, we did not use market wage to evaluate labor cost due to the concern over differentiated labor costs between households who hire in and those who hire out labor. Hence, the estimated net income was not solely a return to land. Finally, consistent with most Ricardian analyses, this study implicitly assumes farmers will adapt by crop switching in the changing climate. Future research could investigate these issues and how responsive the Vietnam agricultural system is to changing climate. Investigating the changing allocation of land would facilitate a better understanding of climate impacts and their implications for policy.

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Chapter 5. Farm-level adaptations to climate change in Vietnam: Investigating the uptake of crop substitution

Abstract: Vietnam is likely to be among the countries hardest hit by climate change. Given the limited capacity for adaptation, crop substitution could be a potential measure to mitigate the effects of climate change. This paper examines the uptake of crop substitution as an adaptation strategy in Vietnam. The data come from the Vietnam Access to Resources Household Surveys, and we model the competition across alternative uses of land using a Fractional Multinomial Logit model. Our empirical findings suggest that Vietnamese farmers have adapted to the changing climate by selecting different crops, and that this adaptation depends on household and farmland characteristics. Increases in winter and summer temperatures mean that farmers are more likely to substitute cereal crops for others. Farms in wet locations with colder winters and cooler summers are likely to choose cash crops. Farmers choose annual industrial crops in locations with warmer springs and autumns. The production of permanent crops requires stable temperatures. The projected climate changes are not likely to jeopardize the national target of maintaining 40 percent of farmland under rice. However, we expect projected climate changes to result in large shifts from cereals to annual industrial crops in the two rice bowls of Vietnam.

Keywords: Climate change, crops, Fractional Multinomial Logit, land use share, Vietnam

5.1. Introduction

Agriculture is sensitive to climate change due to its direct exposure to climate elements. The likely consequences of a changing global climate are more severe in developing countries where the majority of the population is engaged in small-scale farming and have limited ability to adapt (Mendelsohn, 2012; Mendelsohn & Dinar, 1999). As a result, climate change is expected to cause losses to the global yield of rice, maize, wheat, and potatoes

(Yohannes, 2015). Agricultural industries in Africa, Asia, Europe, and the U.S are also sensitive to climate change, even though they have greater ability to adapt (Wang *et al.*, 2009; Maddison *et al.*, 2007; Maddison, 2000; Dinar, 1998; Mendelsohn *et al.*, 1994). This raises a serious concern among governments over prospects of maintaining food security and the likely success of the zero-hunger sustainable development goal set by the United Nations (United Nations, 2015).

The likely negative impacts of climate change on crop production mean countries need to investigate adaptation options and understand how likely farmers are to adapt in response to changes in climate. Adaptation is defined as responses that reduce vulnerability to potential damages from climate change, used by farmers, groups, and governments (Bradshaw *et al.*, 2004). Short-term adaptations include changes in sowing dates, fertilization, and irrigation (Song *et al.*, 2018; Kurukulasuriya *et al.*, 2011; Guo *et al.*, 2010; Pearson *et al.*, 2008; Mall *et al.*, 2004). Long-term adaptations could include crop substitution (Rezaei *et al.*, 2015; Chatzopoulos & Lippert, 2015; Wang *et al.*, 2010; Seo & Mendelsohn, 2008a; Kurukulasuriya & Mendelsohn, 2007; Bradshaw *et al.*, 2004), farm-type selection (Seo, 2010; Mendelsohn & Seo, 2007), or bundling agricultural technologies (Fleischer *et al.*, 2011). The Ricardian approach shows lower damages from the changing climate, while allowing for the actual adaptations farmers make (Thamo *et al.*, 2017; Mendelsohn, 2012; Deschênes & Greenstone, 2012; Mendelsohn & Dinar, 1999).

Although crop substitution is often suggested as a potential adaptation, how likely farmers are to substitute crops has received less attention (Mendelsohn, 2012). Previous cross-sectional analyses have been limited to crop choice in Africa (Kurukulasuriya & Mendelsohn, 2007), Germany (Chatzopoulos & Lippert, 2015), China (Wang *et al.*, 2010), and South America (Seo & Mendelsohn, 2008a). The patterns of adaptation vary greatly from area to area depending on the extent of the changing climate and other socio-economic environments that farmers face. Mendelsohn (2012) expressed the need for research that explores potential adaptation in each scenario of changing climate and socio-economic conditions.

Vietnam is likely to be among the countries hardest hit by future climate change (Dasgupta *et al.*, 2009). Previous Ricardian analyses have shown likely negative impacts of the projected climate changes on this agrarian economy (Trinh, 2018; Le *et al.*, 2015). Crop substitution could be the appropriate adaptation strategy for Vietnam to reduce its vulnerability, given that limited capacity exists for bundling agricultural technologies as Fleischer *et al.* (2011) suggested.

Our study is the first analysis of climate-induced adaptation for Vietnam. As suggested by Mendelsohn (2012, p. 10), we consider the long-term effects of climate variability on selecting crops by looking at how Vietnamese farmers have adapted to the range of climates that exist locally today. Because other dramatic changes are happening in agriculture, it is difficult to detect the subtle impact of climate change using cross-sectional data (Mendelsohn, 2012). For this reason, we use a ten-year panel of household-level data to better control for unobserved heterogeneity when estimating climate impacts and predicting outcomes of land use. In contrast to previous models for crop choice that obtain cross-household evidence, we use a Fractional Multinomial Logit model to reveal the intra-household competition across alternatives in land use. Then we use estimated results to predict how Vietnamese farmers might change the crops they grow in the future. Our research results are important for policy-makers seeking to identify supplementary adaptations to the projected changing climate.

5.2. Research methodology

Modeling farmland allocation in response to changing climate is not an easy task. Land use is the outcome of a decision making process by individual farmers whose behaviour is variable and constrained differently (Chambers & Conway, 1992) depending on a broad range of physical and socio-economic contexts. The complexity of factors affecting land use choice, and their variability from one setting to another complicates the task of predicting land use outcomes and designing land use policy. Previous analyses on crop choice in response to changing climate have applied the Multinomial Logit model (Chatzopoulos & Lippert, 2015; Wang *et al.*, 2010; Seo & Mendelsohn, 2008a, 2008b; Kurukulasuriya & Mendelsohn, 2007). Farm types have been classified into binary choices while each individual farmer is assigned only one alternative. Thus, this modeling approach reduces to cross-household comparisons and does not facilitate identification of factors associated with the intra-household competition across alternatives.

Land use for different crops can be calculated in terms of proportional shares (s_j) which fall between zero and one. The sum of s_j across crops for each household must sum to unity. Given this limited range of values, traditional estimation methods (linear regression, the log-odds ratio) are not appropriate (Ramalho *et al.*, 2011). While predicted values from a linear regression model may lie outside the range (0;1), the log-odds ratio method resorts to an ad-hoc transformation of original data when the actual proportions are extreme values (such as 0% or 100% farmland allocated to a particular crop). Papke and Wooldridge (1996) and Papke and Wooldridge (2008) developed a Fractional Binomial Logit model to deal with fractional variables using the quasi-maximum likelihood estimator (QMLE) without an ad hoc transformation of boundary values in the univariate context.

In a multivariate setting, researchers' main interest is often estimating the conditional means of fractions given a set of explanatory variables. Woodland (1979) proposed the Maximum Likelihood estimation of systems of share equations based on the Dirichlet distribution. However, one disadvantage associated with the Dirichlet distribution for fractional response models is that the predicted values fall outside the unit interval at some particular values of explanatory variables (Murteira & Ramalho, 2016; Mullahy, 2015). The Fractional Multinomial Logit model is an extension of the Fractional Binomial Logit model which jointly models shares in a multivariate setting while taking into account the bounded and fractional nature of shares. The method has been applied in several studies of fractional response variables (see Ramalho *et al.* (2011), Becker (2014), Mullahy (2015), Murteira and Ramalho (2016) for a description of alternative specifications, estimation methods, and applications).

Our research investigates how farmers choose to substitute their crops in response to climate change. We employ the Fractional Multinomial Logit framework to jointly model the competition across land use alternatives. Assume that the ith farmer allocates his farmland to the jth crop with a corresponding share of s_j (j =1, 2,…, J). The conditional mean for land use share for crop j can be expressed in terms of a multinomial logit functional form of linear indexes as:

$$E(s_{ij}|x_i) = G_j(x_i\beta_j) = \frac{\exp(x_i\beta_j)}{\sum_{j=1}^{J} exp(x_i\beta_h)} \qquad j = 1, 2\ldots,J \qquad (5.1)$$

where x_i is a vector of climate and other control variables. Because the relationship between climate and agriculture is nonlinear (Fezzi & Bateman, 2015; Mendelsohn *et al.*, 1994), vector x_i includes square terms of climate variables.

As with the familiar multinomial logit estimator, some normalization is needed as all J of the β_j cannot be separately identified in the multinomial quasi-likelihood (Mullahy, 2015). If we set $\beta_1 = 0$, then we get:

$$E(s_{ij}|x_i) = G_j(x_i\beta_j) = \frac{1}{1+\sum_{h=2}^{J} exp(x_i\beta_h)} \qquad j = 1 \qquad (5.2)$$

And:

$$E(s_{ij}|x_i) = G_j(x_i\beta_j) = \frac{\exp(x_i\beta_j)}{1+\sum_{h=2}^{J} exp(x_i\beta_h)} \qquad j = 2, 3\ldots,J \qquad (5.3)$$

One can define the QMLE for the multinomial logit specification by writing the likelihood contribution of a single agent:

$$\mathcal{L}_i(\beta) = \prod_{j=1}^{J} E[s_{ij}|x_i]^{s_{ij}} \tag{5.4}$$

And the sum of the individual log-likelihoods is maximized to obtain the estimator for β:

$$\hat{\beta} = arg \max_{\beta} \sum_{i=1}^{N} \log \mathcal{L}_i(\beta) \tag{5.5}$$

It is important to note that β_k is no more equal to partial effects as in the linear setting because the weighted sum of other β is used to calculate the partial effects, as illustrated by writing out the partial effect of the kth regressor on the jth share:

$$PE_{ijk} = \frac{\partial E[s_{ij}|x_i]}{\partial x_{ik}} = E\left[s_{ij}\middle|x_i\right].\left[\beta_{jk} - \frac{\sum_{h=2}^{J} \beta_{hk} \exp\,(x_i\beta_j)}{\left[1+\sum_{h=2}^{J} \exp\,(x_i\beta_h\right]}\right] \tag{5.6}$$

However, the average marginal effects (APE) are invariant to the choice of normalization and can be interpreted as the percentage point change in the response outcome given a one-unit increase in the corresponding explanatory variables. The average marginal effect of a continuous independent variable x_k on the jth share (s_j) is expressed as:

$$\widehat{APE}_{jk} = \sum_{i=1}^{N} \left(\frac{w_i}{\sum_{i=1}^{N} w_i}\right) * \widehat{PE}_{ijk} = \sum_{i=1}^{N} \left(\frac{w_i}{\sum_{i=1}^{N} w_i}\right) * \frac{\delta \hat{E}[s_j|x_i]}{\delta x_{ik}} \tag{5.7}$$

where δ is the first derivative, i denotes the observation, w_i are nonnegative weights that may be used to estimate. When no weights are given, the calculation APE in Equation (5.7) uses $w_i = 1$. Due to the adding-up restriction, $\sum_{j=1}^{J} \widehat{APE}_{jk} = 0$. In the case when x_k is a dummy variable, APE_{jk} is the sample average of the derivative:

$$\frac{\partial E[s_{ij}|x_i]}{\partial x_{ik}} = G_j\left[x_{im}\beta_{jm} + \beta_{jk}\right] - G_j\left[x_{im}\beta_{jm}\right] \tag{5.8}$$

where x_m denotes other explanatory variables rather than the dummy variable x_k at the observation i.

Previous cross-sectional adaptation analyses can distinguish the effects of climates from other exogenous variables (Blanc & Reilly, 2017) by assuming the unobserved heterogeneity is time-invariant and identical across crops. However, this strong assumption is unlikely to be relevant for several reasons. Firstly, the constant price assumption underpinned by cross-sectional data can be misleading as it does not allow for year-to-year market shocks (Mendelsohn & Massetti, 2017; Blanc & Reilly, 2017) to have effects on crop choice. Moreover, land use shares for different crops may respond differently to market shocks. We allow for time-varying unobserved factors to have non-uniform effects on land shares in Equation (5.1) using a set of time dummies.

Climate-induced adaptation analyses have shown crops respond heterogenously to temperatures based on the assumption of the additive separability of temperature (Thamo *et al.*, 2017; Chatzopoulos & Lippert, 2015; Kurukulasuriya *et al.*, 2011; Wang *et al.*, 2010; Seo & Mendelsohn, 2008a, 2008b; Kurukulasuriya & Mendelsohn, 2007). If we assume that economic losses caused by rising temperatures can be mitigated by higher levels of precipitation and these interactions vary by crop, then assuming farmers are looking to maximize net utility from their farm by choosing crops among the available set of options, the failure to capture climate interactions potentially results in biased estimates of climate impacts. We relax the assumption of the additive separability of climate effects by introducing climate interactions into Equation (5.1). Household’s crop choices can be correlated over time as the households exhibit unobserved time-constant characteristics. We allow for serial correlation in household’s land allocation by clustering the Fractional Multinomial Logit model by household to get precise estimates of standard errors. The following section describes the data we used in this analysis.

5.3. Data

Our primary data come from the Vietnam Access to Resources Household Surveys (VARHS) 2006–2016. The nationally representative surveys a once every two years to collect information on several aspects of income activities including, but not limited to, agricultural production across regions in Vietnam. Details on crop production were collected on the plot-level that makes it feasible to calculate land use shares for different crops. The combination of these surveys generates an unbalanced ten-year panel of 11,829 year-households with complete information. The fixed-effects model cannot work well with data for which cluster variation is minimal or for slowly changing variables such as different selections of crops or farm size (Bell & Jones, 2015; Gormley & Matsa, 2013; Wooldridge, 2010). Thus we pool the data across years and allow for time-varying shocks to have different effects on crops.

We use data on plot-level production of 19 types of crops to classify typical household crop choice in Vietnam. We group crops into five mutually-exclusive categories: (1) Cereals, including rice and maize; (2) Cash crops, including potatoes, sweet potatoes, cassava, and vegetables; (3) Annual industrial crops, including peanuts, beans, soybeans, sugar canes, and other annual industrial crops; (4) Fruit; (5) Permanent industrial crops, including coffee, rubber, pepper, cashew, and other permanent industrial crops.

We classify crop choice based on these crops needing different climatic and farmland conditions to grow. The first three groups are short-lived crops which are normally grown more than once in an agricultural year. Cereals are temperature-tolerant but drought-sensitive normally grown on flat parcels. Cash crops are temperature-sensitive and require water in all growth periods. Annual industrial crops require less irrigation and can be grown on parcels with slopes. The last two groups comprise permanent crops that prefer high temperatures. Fruit trees, however, require a high level of humidity while more rainfalls are associated with losses to permanent industrial crops in some particular periods. The rising global temperature can shorten the growth cycle of most annual crops (Batts *et al.*, 1997). Changing climate is, therefore, expected to have more pronounced impacts on the selection of annual crops.

Table 5.1. Variable definition

Variable	Measurement
Land use shares	
(1) Cereals (2) Cash crops (3) Annual industrial crops (4) Fruit (5) Permanent industrial crops	The proportion of farmland in household's total farming area allocated to the corresponding crop group (%)
Household characteristics	
hh_size	Number of household member (person)
head_age	Age of household head (year)
head_edu	Formal schooling of household head (years)
head_sex	Dummy, =1 if male for household head
born_in_commune	Dummy, =1 if either household head or spouse born in the commune
ethnic	Dummy, =1 if Ethnicity of the household is Minority
remittances	Remittances from household members (2010 million VND)
Farmland characteristics	
no_plots	Number of separate farmland plots
farm_size	Farm size (1000 square meter)
irrigation	% of farmland irrigated
tenure	% of farm land owned by the household
Socio-economic characteristics	
extension	*Number of extension contacts during the last two years (times)*
population	Population density (thousand persons/square kilometer)
credit	Dummy, =1 if household resorted to credit loan in the year
Topographic characteristics	
elevation	Meter
Climate variables	
winter_tem	Winter monthly temperature (Celsius degree)
spring_tem	Spring monthly temperature (Celsius degree)
summer_tem	Summer monthly temperature (Celsius degree)
autumn_tem	Autumn monthly temperature (Celsius degree)
winter_pre	Winter monthly precipitation (millimeter)
spring_pre	Spring monthly precipitation (millimeter)
summer_pre	Summer monthly precipitation (millimeter)

autumn_pre	Autumn monthly precipitation (millimeter)
Regional dummies	Red River delta, Northeast, Northwest, Northern Central, Southern Central, Central Highlands (the Mekong delta as base)
Time dummies	2008, 2010, 2012, 2014, 2016 (2006 as base)

The analysis includes a broad set of climate and other control variables suggested in the literature on land use choice (Fisher-Vanden *et al.*, 2013; Mendelsohn, 2012; Seo & Mendelsohn, 2008a; Lesschen *et al.*, 2005; Browder *et al.*, 2004; van Ittersum *et al.*, 1998; Walker & Homma, 1996). These variables include household characteristics, farmland characteristics, and socio-economic characteristics. Table 5.1 presents a brief definition of the variables. These variables are derived from the VARHS datasets. Unobserved heterogeneity across regions in terms of soil properties and agricultural policy may affect land use decisions. However, these data are not available to be included in this research. Instead, a set of region dummies is used to capture unobserved differences across regions.

We derive the climate data with a high resolution of one-square kilometer from Worldclim version 2.0 (Fick & Hijmans, 2017). We do not include climate data for twelve months in the analysis for the reason that there is multicollinearity between monthly climates. Instead, this study uses seasonal averages of temperature and rainfall for the period 1970-2000 to support the identification of heterogeneous climate impacts on land use allocation. Climate and agricultural production may vary across latitudes (Mendelsohn *et al.*, 1994). We extract data on elevation with the same resolution on a commune-level basis using free spatial data from DIVA-GIS website.

Table 5.2 provides a general picture of the land use across regions while Table 5.3 presents the main statistics of independent variables used in the analysis. Cereals and permanent industrial crops are the most popular choices by Vietnamese farmers. In the Red River and Mekong River deltas where irrigation covers more than 70% of the cropping area, farmers maintain a high proportion of cereals of more than 65% in their total farming area.

Permanent industrial crops, including coffee, are the most popular choice by farmers in the Central Highlands where the climate is cool and stable. Cash crops are favored by farmers in the Central Highlands, Northwest, and Northeast where the average temperatures are lower than the national averages. Annual industrial crops have higher proportions in locations with hotter climate and less rainfall such as the Northern Central and Southern Central. The Mekong River delta and the Central Highlands are also homes to fruit trees as these regions exhibit high proportions of farmland allocated to fruit crops. Land fragmentation is pervasive as an average household cultivates 4.2 different plots (Table 5.3). There exist systemic differences in seasonal climates as the 30-year averages are different. There has been little rainfall in the winter (34 millimeters per month) while the summer has been experiencing the highest precipitation but with much volatility across regions.

Table 5.2. Land use share for crops, by region (%)

Region	Cereals	Cash crops	Annual industrial crops	Fruit	Permanent industrial crops
Red River	81.18	6.88	7.15	2.90	1.90
Northeast	74.02	11.08	7.24	2.15	5.52
Northwest	77.70	13.52	2.91	3.12	2.76
Northern Central	62.73	11.72	10.80	9.34	5.41
Southern Central	63.57	9.51	10.78	9.61	6.54
Central Highlands	38.02	11.83	3.89	9.76	36.49
Mekong River	65.27	5.45	10.31	12.91	6.07
Total	63.87	9.85	7.20	6.67	12.42

Table 5.3. Statistics of variables				
Variable	Mean	Std. Dev.	Min	Max
Household characteristics				
hh_size	4.49	1.84	1.00	16.00
head_age	52.27	13.10	16.00	99.00
head_edu	6.76	3.73	0.00	13.00
head_sex	0.82	0.39	0.00	1.00
born_in_commune	0.81	0.39	0.00	1.00
ethnic	0.60	0.49	0.00	1.00
remittances	5.93	20.56	0.00	0.59
Farm land characteristics				
no_plots	4.21	2.89	1.00	25.00
farm_size	8.28	13.41	0.25	21.03
irrigation	0.71	0.4	0.00	1.00
tenure	0.62	0.44	0.00	1.00
Socio-economic conditions				
extension	1.34	2.07	0.00	57.00
population	550.46	711.13	35.00	2,182.00
credit	0.59	0.49	0.00	1.00
Topographic condition				
elevation	209.77	273.51	0.00	1,188.80
Climatic conditions				
winter_tem	19.63	3.16	11.78	26.33
spring_tem	24.73	1.94	18.62	29.16
summer_tem	27.38	1.95	20.91	29.67
autumn_tem	24.31	1.63	18.49	27.63
winter_pre	34.07	30.93	11.14	128.59
spring_pre	94.36	26.5	37.62	146.95
summer_pre	235.25	77.34	87.89	433.55
autumn_pre	198.59	85.98	64.59	417.76

5.4. Estimation results

The estimation of the system of land use equations is performed on the household-level panel data using Equation (5.1) with a set of time dummies and climate interactions. Albeit small, the panel evidence suggests within-household variations in crop shares across years. These variations lend credence to the need to control for time-varying factors associated with land use decisions by farmers suggested by Mendelsohn (2012). Our Fractional Multinomial Logit estimates show statistical significance of the estimates for these time dummies and interactions. We conduct a series of tests to determine whether the convention of assuming constant effects unobserved heterogeneity and homogenous climate climate interactions on crop choice is relevant for our analysis. Table 5.4 reports a series of tests using the Likelihood Ratio tests (LR).

Table 5.4. Testing for hypotheses on time-varying unobserved factors and climate interactions

Null hypothesis	Variable on which its coefficients are tested	Value to be tested	Chi2 test *(p-value)*			
			Cash crops	Annual industrial crops	Fruit	Permanent industrial crops
(1) Constant effect of unobserved time-varying factors on crops	Time dummies	Equality on each share	159.90 (0.000)	62.46 (0.000)	154.46 (0.000)	253.04 (0.000)
(2) Uniform effect of unobserved time-varying factors on crops	2008	Equality across shares	56.41 *(0.000)*			
	2010	Equality across shares	106.76 *(0.000)*			
	2012	Equality across shares	184.61 *(0.000)*			
	2014	Equality across shares	258.56 *(0.000)*			
	2016	Equality across shares	293.97 *(0.000)*			
(3) Homogenous climate interaction effect on crops	Winter_tem x Winter_pre	Equality across shares	7.93 *(0.047)*			
	Spring_tem x Spring_pre	Equality across shares	11.39 *(0.009)*			
	Summer_tem x Summer_pre	Equality across shares	32.31 *(0.000)*			
	Autumn_tem x Autumn_pre	Equality across shares	4.14 *(0.246)*			

The first test is on the assumption of constant effect of unobserved time-varying factors on each land use share which means the estimated coefficients of time dummies are equal for a particular share. The second test is on the hypothesis of uniform effect of unobserved time-varying factors across different shares. These two hypotheses are taken from previous crop choice analyses (Chatzopoulos & Lippert, 2015; Oczkowski & Bandara, 2013; Wang *et al.*, 2010; Seo & Mendelsohn, 2008a; Kurukulasuriya & Mendelsohn, 2007). The LR tests reject the null hypotheses at the conventional level. Therefore, the use of time-dummies and allowing them to have different estimates in our Fractional Multinomial Logit model is expected to isolate the confounding effects of external changes out of climate impacts. The third test contrasts climate interactions across land use alternatives. The LR tests justify the significance of climate interactions in our analysis as they indicate heterogeneous climate interactions on crops in three out of the four seasons.

Table 5.5 reports the QMLE estimates of the Fractional Multinomial Logit model controlling for unobserved time-varying effects and climate interactions. We set the first response outcome – the share of cereals – as the base outcome in the estimation process. The estimated coefficients for climate variables and their square terms are statistically significant for at least one seasonal climate indicating the non-linear response of crops to climate. The estimated coefficients of time dummies are strongly significant for most of the land use shares suggesting statistical influences of external changes such as market prices and agricultural policy on land use decisions in the studied period. Estimates for household characteristics also show statistical significance in land share equations. Increases in household size, age, education, and remittances are associated with higher proportions of farmland allocated to other crops rather than to cereals. Land fragmentation, measured by the number of farmland plots, in contrast, is found to induce land use shifts from annual industrial crops and permanent crops to cereal production. Better irrigation increases the proportion of farmland allocated to cereals as the estimated coefficients of this variable are negative in all land share equations.

Table 5.5. Fractional Multinomial Logit estimates of variables

Variables	Cash crops	Annual industrial crops	Fruit	Permanent industrial crops
winter_tem	-2.099	-2.959*	-0.588	-0.790
winter_tem square	0.040	0.035	-0.003	0.013
spring_tem	0.494	-2.848	1.621	-0.489
spring_tem square	0.006	0.071	-0.016	0.006
summer_tem	-4.583**	-9.370***	5.143	1.745
summer_tem square	0.077*	0.150***	-0.090	-0.013
autumn_tem	7.814**	7.636**	0.317	3.153
autumn_tem square	-0.151**	-0.110	0.027	-0.033
winter_pre	-0.040	-0.101	-0.288***	-0.089
winter_pre square	-0.000	0.000**	-0.001**	-0.000
spring_pre	-0.024	-0.145*	0.142*	0.009
spring_pre square	0.000***	-0.000	-0.000	-0.000
summer_pre	0.010	-0.037	0.143***	0.221***
summer_pre square	-0.000	0.000	-0.000**	-0.000***
autumn_pre	0.034	0.106**	0.123**	0.078*
autumn_pre square	-0.000**	-0.000*	0.000	-0.000*
winter_tem * Winter_pre	0.004	0.004	0.018***	0.010**
spring_tem * Spring_pre	-0.002	0.006**	-0.005*	0.001
summer_tem * Summer_pre	0.000	0.002	-0.004***	-0.006***
autumn_tem * Autumn_pre	-0.000	-0.003	-0.006***	-0.003*
elevation	0.001	0.002	-0.001	0.003**
hh_size	0.009	-0.049**	0.006	-0.003
head_age	0.009***	0.010***	0.011***	0.005
head_edu	0.014	0.032***	0.017	-0.001
head_sex	0.013	-0.017	0.239**	0.200*
born_in_commune	0.330***	-0.087	0.922***	0.301**
ethnic	-0.060	0.498***	0.218**	0.193**
remittances	-0.000	0.001	0.004***	0.001
no_plots	0.015	-0.004	-0.085***	-0.043***
farm_size	-0.005	0.005	-0.009**	0.014***
tenure	-0.071	-0.618***	0.066	0.074
irrigation	-0.470***	-0.658***	-0.466***	-0.499***
extension	-0.001	0.009	0.019	0.010
population	0.000	-0.001***	-0.000	0.000**
credit	-0.080	-0.021	0.008	0.073
I_2008	-0.850***	-0.970***	16.815	0.558***
I_2010	-0.365***	-0.783***	17.932	1.796***
I_2012	0.104	-1.123***	17.660	2.020***
I_2014	-0.629***	-1.592***	16.989	2.202***
I_2016	-0.676***	-1.450***	16.778	2.490***
Constant	-29.151	88.706***	-137.591***	-89.186**
Regional dummies			Yes	
Observations	11,829	11,829	11,829	11,829

**** p<0.01, ** p<0.05, * p<0.1.*
(Standard errors are clustered at household-level to account for panel structure)

Owing in part to the normalization, interpreting the Fractional Multinomial Logit estimates is difficult. Moreover, the inclusion of the square terms of, and interactions between seasonal climates makes the signs and magnitudes of individual coefficients no longer fully represent the effects of each climate phenomenon. Therefore, we derived the average marginal effects of continuous predictors using Equation (5.7) and binary variables using Equation (5.8). Table 5.6 reports the estimated average marginal effects of one unit change in explanatory variables on land use shares.

Table 5.6. Average Marginal Effects of variables on land shares

	Cereals	Cash crops	Annual industrial crops	Fruit	Permanent industrial crops
winter_tem	0.091**	-0.024	-0.090***	0.007	0.016
spring_tem	-0.107***	0.043**	0.072***	0.013	-0.021
summer_tem	0.086**	-0.016	-0.038**	-0.026	-0.006
autumn_tem	-0.153**	0.016	0.092***	-0.002	0.047
winter_pre	-0.008***	0.001	-0.001	0.001	0.007***
spring_pre	0.000	0.000	0.000	0.000	0.000
summer_pre	-0.002***	0.001**	0.000	0.001***	0.000*
autumn_pre	0.001*	0.000	0.001**	0.000	-0.002***
elevation	0.000*	0.000	0.000	0.000	0.000**
hh_size	0.002	0.001	-0.003***	0.001	-0.001
head_age	-0.002***	0.001***	0.001***	0.000***	0.000
head_edu	-0.003**	0.001	0.002***	0.001	-0.001
head_sex	-0.017	-0.003	-0.003	0.011**	0.012
born_in_commune	-0.061***	0.020**	-0.013	0.047***	0.008
ethnic	-0.036***	-0.013*	0.030***	0.008	0.010*
remittances	0.000	0.000	0.000	0.000***	0.000
no_plots	0.004***	0.002***	0.000	-0.004***	-0.002**
farm_size	0.000	-0.001**	0.001	-0.001***	0.001***
tenure	0.028***	-0.003	-0.039***	0.006	0.008
irrigation	0.098***	-0.026***	-0.034***	-0.015***	-0.023***
extension	-0.001	0.000	0.000	0.001	0.000
population	0.000	0.000	0.000***	0.000	0.000***
credit	0.002	-0.008	-0.001	0.000	0.006

While household size (a proxy for family labor) is not statistically significant for most of the crop shares, it is significant and negative for annual industrial crops. If the number of family members were to increase by one person, the proportion of farmland allocated to annual industrial crops would decrease by 0.3% (-0.003), holding other variables constant. Age of the household head is significantly associated with increases in the shares for cash crops and annual industrial crops. Farmers with higher education are likely to allocate more farmland to annual industrial crops and fruit rather than to cereals.

The proportions of farmland under cereals, cash crops, and annual industrial crops are likely to be lower for male-headed households although the estimated average marginal effects are not statistically significant. Being born in the current commune is expected to have effects on the choice of traditional crops in the commune. In comparison with migrant households, a born-in-commune household allocates a 6.1% less of their farmland to cereals. Ethnic Minority households spend a 3.6% less of their farming land on cereal production as it is well known that they are familiar with fruit and other permanent crops while Kinh people have a long tradition with rice farming. Remittances from household members are expected to increase investments in crops with longer horizons. However, the results show that average marginal effects are minimal on all land use shares.

Farmland characteristics are found to influence land use choice given the Vietnam context. Land fragmentation is associated with lower proportions of farmland allocated to fruit and perennial industrial crops. A one-unit increase in the number of farmland parcels, in contrast, is associated with a 0.4% and 0.2% increase in farmland area allocated to cereals and cash crops, respectively. The results show no size-biases in land allocated to different crops as the marginal effects are minimal. Farmers may expect that future benefits from investments in long-term crops will mostly accrue to the landowner rather than to themselves (Knowler *et al.*, 2001), improvements in land ownership are found to shift land use patterns towards high-value perennial crops. Improvements in irrigation, in contrast, are likely to shift the land use towards cereal production which requires better irrigation and is exposed to lower production risk due to short cropping time. The estimated average marginal effects of socio-economic conditions such as extension services, population pressure, and credit availability are minimal and not statistically significant for most of the land use choices.

The variables of our special interest are seasonal climates. Table 5.6 shows that the once precipitation and other factors have been controlled for, land use shares for fruit and other permanent industrial crops are less responsive to changes in temperatures as the average marginal effects are small and not statistically significant. As expected, the choices of cereals, cash crops, and annual industrial crops, in contrast, are very sensitive to changing temperatures. The effects of seasonal temperatures are highest for cereals. A one uniform increase in annual temperature ($1^{\circ C}$) is likely to be associated with an 8.3% reduction in farmland allocated to cereals, while the shares for cash crops and annual industrial crops are expected to increase by 1.9% and 3.6%, respectively.

Once irrigation has been controlled for, the choice of crops is found to be less sensitive to precipitation than to temperature. Although the estimated average marginal effects of seasonal rainfalls are statistically significant for most crops, the estimated magnitudes are minimal. This insight is consistent with finding from Oczkowski and Bandara (2013) who found minor impact of rainfall on land allocation in Australia. A wetter winter is likely to induce the shift from cereals to permanent industrial crops and cash crops which prefer high humidity. A 1 millimeter increase in summer precipitation is associated with a 0.2% decrease in the area allocated to cereals. Farms in locations with wetter autumns are likely to choose cereals and tend to eschew permanent industrial crops.

Looking at the distribution of seasonal climate effects, farms in locations with warmer and drier winters, and hotter and drier summers tend to choose cereals. Cash crops are favored by farmers in regions with colder and wetter winters, and cooler and wetter summers. Warmer springs and autumns are associated with increases in the share for annual industrial crops. Farms in wetter locations with warmer winters and cooler summers are likely to choose fruit trees. The production of permanent industrial crops does not require much water but stable temperatures. Farmers in regions with warmer winters ad cooler summers tend to allocate their farming land to permanent industrial crops.

5.5. Simulation of land use change

The previous section has illustrated how Vietnamese farmers have adapted to the changing climate in terms of crop choice. Changes in seasonal temperatures and precipitations are associated with different responses in terms of crop selection by farmers. Vietnam is expected to be among the countries hardest-hit by future climate change (Dasgupta *et al.*, 2009). A report by the Ministry of Natural Resources and Environment (MONRE, 2009) indicates non-uniform changes in climate patterns. Annual temperatures are projected to increase by 0.4°C to 3.2°C between 2030 and 2100 while the increases in the winter and the spring are higher than those in the summer and the autumn. The Northern region will experience faster increases in seasonal temperatures. Regional and national averages of precipitation are projected to increase but with different patterns for seasons. It is, therefore, interesting to understand how Vietnamese farmers might adapt to the projected changes in climate patterns in terms of crop choice.

In this section, we attempt to predict how Vietnamese farmers might switch crops in response to the projected climate changes developed by the Ministry of Natural Resources and Environment (MONRE, 2009) under the medium emission scenarios. We assume no significant changes in factors which can result in changes in the relative profitability of the studied crops. Rather, this simulation is an effort to measure how farmers might allocate their farming land in response to the projected climate scenarios. The ten-year evidence used in this Fractional Multinomial Logit model is assumed to be appropriate to predict future changes in land use allocations. In addition, we assume the average marginal effects for the observed ranges of climate variables remain constant in the future and use the estimated parameters from Table 5.5 for the simulation. We do not assume uniform changes in climate patterns across seasons and regions. Instead, we allow seasonal climates to vary by region to better understand the effects of the projected changes in land use. Table 5.7 presents the results.

Table 5.7. Projected changes in land allocations, 2030 – 2100 (%)

	Cereals	Cash	Annual	Fruit	Permanent
Baseline (%)	*63.87*	*9.85*	*7.20*	*6.67*	*12.42*
Fitted values (%)	*63.87*	*9.85*	*7.20*	*6.67*	*12.42*
			2030		
Red River delta	-9.79	2.13	3.09	1.59	2.97
Northeast	-9.08	1.63	2.29	1.34	3.82
Northwest	-11.72	2.31	3.84	1.67	3.91
Northern Central	-9.75	2.14	4.47	0.48	2.66
Southern Central	-3.09	1.17	4.61	-0.15	-2.53
Central Highlands	-2.07	0.86	2.10	-0.19	-0.69
Mekong River delta	-4.02	1.16	3.54	-0.77	0.09
Total	-5.00	1.34	3.58	0.05	0.03
			2050		
Red River delta	-20.93	4.77	7.96	3.13	5.07
Northeast	-19.42	3.58	6.57	2.43	6.84
Northwest	-19.18	3.59	5.35	3.12	7.11
Northern Central	-18.93	4.62	9.18	0.99	4.14
Southern Central	-4.25	1.83	7.80	-0.37	-5.01
Central Highlands	-3.44	1.36	3.84	-0.49	-1.28
Mekong River delta	-8.17	1.80	7.36	-1.60	0.61
Total	-9.21	2.34	6.88	0.00	-0.01
			2100		
Red River delta	-35.56	7.59	11.56	5.54	10.87
Northeast	-35.81	6.44	10.41	4.93	14.04
Northwest	-37.71	6.86	10.30	5.96	14.58
Northern Central	-30.98	7.06	13.56	1.48	8.88
Southern Central	-12.84	4.66	17.70	-0.37	-9.15
Central Highlands	-8.92	3.25	8.14	-0.60	-1.88
Mekong River delta	-17.71	4.15	14.61	-2.23	1.18
Total	-19.36	4.89	13.64	0.36	0.47

(Total changes in land use shares are area-weighted averages of the projected changes in regional

The projected climate changes in the short-term, 2030, are likely to induce a 5% shift of total farmland under cereals to mainly annual industrial crops and cash crops. The combined effects of further increases in seasonal temperatures and more severe shortages of rainfalls in the distant future, 2050 and 2100, are associated with large reductions in land use share for cereals. In 2100, the whole country is likely to experience a redistribution of 19.36%

of cereal area to annual industrial crops (13.64%) and cash crops (4.89%). The farmland areas under permanent crops are expected to witness minimal responsiveness.

The distribution of climate impacts across regions indicates heterogeneous adaptation responses in terms of crop choice by farmers. The Central Highlands is characterized by a cool and stable climate. The expected increases in temperatures and rainfalls are not likely to result in significant changes in land use choice as the estimated impacts remain small over time. The non-uniform changes in seasonal climate in the Northern regions, including the Red River delta, the Northeast, the Northwest, and the Northern Central, are predicted to result in large reductions of farmland under cereals, ranging from 9% to 36% between 2030 and 2100. In contrast to the Central Highlands and the Southern Central where reductions in permanent industrial crops are expected, the reductions in cereals in the Northern regions are mostly distributed to long-term investments in permanent industrial crops and annual industrial crops. The Mekong River delta is the largest rice area of the country accounting for 50% of domestic rice production and 90% of export. The projected increases in temperature and reductions in precipitation in the long-term are likely to induce large shifts from rice to annual industrial crops which are more drought-tolerant.

The Vietnam government is concerned with food security given the rising demand for food and the declining food growth rate. According to the Resolution on national food security (No. 63/NQ-CP), Vietnam must keep at least 3.8 million ha of rice land to meet domestic and export demands in 2020. Rutten *et al.* (2014) highlighted that although this target would not be jeopardized in the short-term even in high climate impact scenarios, the conversion of paddy rice land into other uses would continue in the future. Our simulation of farmers' behaviour in response to the projected climate change also confirms the likely conversion of cereal areas into other crop types in the future.

5.6. Concluding remarks

This empirical analysis employed a Fractional Multinomial Logit model to capture the responsiveness of Vietnam land use choice to changing climate. The model was estimated on nationally representative data on crop production. The results underpinned the importance of household and farmland characteristics on land use decisions. Age and education are negatively correlated with the shares of farming land allocated to cereals and are associated with higher shares for other crops. Ethnic Minority people are likely to allocate more farmland to perennial crops while Kinh people tend to maintain higher production of cereals. Land fragmentation is associated with the choice of cereals and other annual crops over perennial crops. Better irrigation is estimated to increase the share utilized for food production.

The allocation of farmland in Vietnam is found to be sensitive to climatic conditions, which is in line with empirical findings for China (Wang *et al.*, 2010), Germany (Chatzopoulos & Lippert, 2015), South America (Seo & Mendelsohn, 2008a), and Africa (Kurukulasuriya & Mendelsohn, 2007). Seasonal climates exert heterogeneous impacts on land use shares for different crops. Increases in winter and summer temperatures shift the farmland towards cereals. Cash crops are preferred in wet locations with colder winters and cooler summers. Farms in locations with warmer springs and autumns tend to opt for annual industrial crops. The production of permanent crops including fruit trees and permanent industrial crops requires stable temperatures. These crops are preferred by farms in locations with warmer winters and cooler summers. The simulation indicates large shifts in total farming areas allocated to cereals in the period 2030-2100.

Vietnam agriculture is facing challenges given the predicted future climate changes. Agricultural land is predicted to decline by 13% as a result of a one-meter increase in sea level (Dasgupta *et al.*, 2009). Our simulation also indicates large shifts in land use shares from cereals towards other crops in the Red River and Mekong River deltas which are the two rice bowls of the country. This underscores the need for the Vietnamese government to develop adaptation policies. Given the likely reductions in cereal areas, improvements in food productivity are vital to maintaining food security and export status. The designation of agricultural policy should also accommodate the likely changes in irrigation demand and investment requirements associated with the conversion of farmland across alternatives.

This analysis attempted to quantify the impacts of climate change on Vietnam land use choice. The interpretation of the results should be done with care as there are several caveats. First, the simulation of land use change was based on the hypothesis that climatic variables are the only ones that change in the future. Although this Fractional Multinomial Logit model was estimated on a broad range of crops in Vietnam, this analysis did not consider new crops that might be introduced into the crop portfolio. Second, we assumed no switching cost across crop types. This is not the case when farmers shift from cereals or other annual crops to perennial crops such as fruit and permanent industrial crops that require heavy capital investments. Further, the research did not take account of any prices effects associated with production changes.

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Chapter 6. Conclusion of the thesis

6.1. Introduction

Vietnam has undergone an intensive transformation from a centrally planned economy to a market-oriented economy since the economic reforms in the mid-1980s. Yet, agriculture is still an important sector supporting employment and income for a large proportion of the population (General Statistics Office, 2016). Future prospects for improving agricultural productivity are potentially constrained as the easy part of the Green Revolution has been achieved. Vietnam is expected to be among the countries most affected by future climate change (Dasgupta *et al.*, 2009). The small-scale production with low adaptation capacity makes it more vulnerable to changing production conditions. This thesis consists of four studies that investigated the dynamics of Vietnam agriculture under changing production conditions. The primary data for the three empirical analyses came from the Vietnam Access to Resources Household Surveys 2006 – 2016.

The first study systematically overviewed the transformation of Vietnam agriculture during the second half of the twentieth century to provide a better understanding of current performance. It applied an historical approach to explaining the dynamics of agriculture, with an emphasis on the rice sector, and its future challenges. The study also sought to explain previous thoughts on regional discrepancies between the two important deltas of Vietnam.

The second analysis explored the impacts of hybrid rice technology in Vietnam in the post-Green Revolution time. The Probabilistic Data Record Linkage method was applied to household survey data to generate a balanced ten-year panel for the study. The adoption of hybrid rice varieties was modelled by a probit model while a panel stochastic frontier model was estimated on a matched sample to shed light on the impacts of hybrid rice on productivity. The analysis contributed to the existing literature on productivity impact assessment in the rice sector and provided inferences regarding the development of the Vietnamese rice technology.

The third study quantified the economic impact of climate change on Vietnam agriculture. The Ricardian function was estimated from data on agricultural production of 20 crops which have been typically produced across regions in Vietnam. In contrast to prior panel Ricardian analyses (Trinh, 2018; Fezzi & Bateman, 2015; Massetti & Mendelsohn, 2011; Deschenes & Greenstone, 2007) assuming uniform market shocks on households, our analysis allowed market shocks to have heterogenous effects on households with different crop portfolios across regions. The two-stage Hsiao method was applied to estimate the likely impacts of marginal and non-marginal changes in long-term climate.

The fourth analysis captured the sensitivity of the Vietnam land use system to climate change. The Fractional Multinomial Logit model was employed to investigate the effects of climates on land use shares for different crops. This is the first crop choice model which allowed for heterogeneous price feedbacks on different land use alternatives when estimating the responsiveness of land use choice to changing climate. The heterogeneous impacts of climate conditions were allowed by proper classifications of seasonal climates. Nonlinear impacts of climate were taken into account. The analysis also took the heterogeneity of household farmland conditions into account by clustering the Fractional Multinomial Logit model to get better results.

6.2. Key findings and policy implications

6.2.1. Productivity impacts of hybrid rice seeds in Vietnam

On-farm experiments have reported productivity gains from hybrid rice seeds. Significant amounts of funding have been allocated to imported hybrid rice despite several production failures. Our analysis is among the first hybrid rice assessments using panel data, and is the first hybrid rice assessment for Vietnam. The analysis provided a simple way to address selectivity bias by combing the Propensity Score Matching with fixed-effects estimators. The stochastic frontier model allowed rice production technologies to differ to lend itself to further assessment of technology impacts on the base productivity, factor productivity, and technical efficiency.

Key findings

The adoption literature often emphasizes the importance of farmland and household characteristics in explaining adoption of agricultural innovations (Pannell & Zilberman, 2020; Norton & Alwang, 2020; Montes de Oca Munguia & Llewellyn, 2020; Llewellyn & Brown, 2020; Chavas & Nauges, 2020; Doss, 2006; Sunding & Zilberman, 2001; Feder & Umali, 1993; Feder *et al.*, 1985). This analysis showed little evidence of self-selection into hybrid rice of farmers. In fact, the results indicate no size-biases in the adoption of hybrid rice seeds as they are a lumpy technology that is easy to adopt on a small scale with minimal start-up cost and no fixed investment. Land fragmentation, in contrast, is associated with a higher propensity towards hybrid rice seed application. Market-oriented farmers tend to eschew adoption of hybrid rice as a result of perceived lower quality and marketability.

Previous assessments have reported significant yield advantages of hybrid rice seeds (Food and Agriculture Organization, 2014; Aldas & Hossain, 2003; Jin *et al.*, 2002; Huang & Rozelle, 1996). However, our analysis shows that although the responsiveness of hybrid rice seeds is higher for some certain inputs, hybrid rice provided a lower base productivity for Vietnam between 2006 and 2016. The results also suggest an inward neutral technology shift due to the replacement of traditional transplanting. Although technical efficiencies are higher for adopters of hybrid rice varieties, average technical efficiency of Vietnam rice farming is still low. An estimate of technical efficiency score of 72% suggests a 39% managerial gap. Our stochastic frontier models indicate that the failure to address selection bias is a source of biased estimates. Productivity impact assessments therefore should take into account selection on observables and unobservables.

Policy implications

Vietnam rice seed technology needs improvements in both productivity potential and quality of hybrid rice varieties. There is no size bias or self-selection in adoption indicating no need for diversified extension activities toward different groups of farmers. While hybrid rice seeds provided no productivity gains, the period 2006-2016 witnessed also a stagnancy in other farming technologies. The development of factor-bias technology is crucial for improved agricultural productivity and the release of agricultural labor into other sectors. Vietnam has the potential to improve rice productivity. An estimate of technical efficiency score of 72 % suggests a 39% managerial gap to be materialized. Improvements in extension services can be important to uplift Vietnam rice productivity.

6.2.2. Impact of climate change on Vietnam agriculture

This analysis made use of high-quality data from the Vietnam Access to Resources Household Surveys. The Probabilistic Data Record Linkage method was applied to generate a ten-year panel on crop income which was used as the dependent variable in the Ricardian analysis. Climatic and geographic data with high resolution were extracted to match with households' location. The Ricardian model was estimated on the panel using the two-stage Hsiao method. In contrast to most previous panel Ricardian analyses assuming uniform market shocks across households, our Ricardian model allowed variations in agricultural markets to have differentiated effects on households with different crop choices. This allows better insights into how variations in climate conditions affect agricultural production.

Key findings

While the failure to account for heterogeneous price feedbacks produces biases to climate estimates, the consequences of ignoring climate interactions are even more severe when estimating climate impacts for Vietnam. This finding is in line with plant physiology (Morison, 1996; Monteith, 1977) and the findings by Fezzi and Bateman (2015) for Great Britain. Ricardian analyses should, therefore, take interactions between climates into account.

The Ricardian results highlight the nonlinear, seasonal role of changing temperature and precipitation. Rising seasonal temperatures are associated with losses to most regions, with spring temperature being the exception. Increases in summer precipitation are valuable to mitigate the negative impacts of rising temperature. The climate simulation indicates marginal losses to agricultural productivity, both in the short term and the long term. Regions with cool climates such as the Central Highlands and the Northwest are likely to be affected the most. The Red River delta, in contrast, is hardly affected at all.

Policy implications

Although changing climate is expected not to cause severe losses, variations in seasonal climates exert production risks especially for mountainous regions with cool climates and lower irrigation coverage. The development of irrigation system is expected to reduce the vulnerability of agriculture to changing climate.

6.2.3. Farm-level adaptations to climate change in Vietnam

Previous Ricardian analyses have shown heterogeneous economic impacts of projected climate change on this agrarian economy (Trinh, 2018; Le *et al.*, 2015). Quantitative assessments on how Vietnamese farmers have allocated their farmland in response to changing climate are absent for Vietnam. This analysis focused on how Vietnamese farmers have adapted to the changing climate by means of crop substitution. Estimated results were then used to predict changes in land use patterns in response the projected changes in short-term and long-term climate.

Key findings

Our Fractional Multinomial Logit model confirms the significance of heterogeneous market shocks and climate interactions on land use alternatives. Adaptation analyses, therefore, should take potentially differentiated effects of these drivers into account when modelling the sensitivity of land use choice to climate.

The analysis revealed the importance of household and farmland characteristics on the choice of crops in Vietnam. Age and education are negatively correlated with the shares of farming land allocated to cereals and are associated with higher shares for other crops. Ethnic Minority people are likely to allocate more farmland to perennial crops while Kinh people tend to maintain higher production of cereals. Land fragmentation is associated with the choice of cereals and other annual crops over perennial crops. Better irrigation is estimated to increase the share utilized for food production.

The Vietnam land use system is sensitive to changing climate. In other words, Vietnamese farmers have adapted to the current climate by means of crop selection for their farmland. Increases in winter and summer temperatures shift the farmland towards cereals. Cash crops are preferred in wet locations with colder winters and cooler summers. Farms in locations with warmer springs and autumns tend to opt for annual industrial crops. The production of permanent crops including fruit trees and permanent industrial crops requires stable temperatures. These crops are preferred by farms in locations with warmer winters and cooler summers. The projected climate changes are expected to induce large shifts from food production to other crops between 2030 and 2100 with a rate of between 5% and 19%. However, these expected land use shifts would not jeopardize the target of maintaining land use for rice production in the future.

Policy implications

Improvements in irrigation system are likely to be effective in reducing the conversion of farmland under food production, especially in the autumn. In the long term, improvements in the relative profitability of food production are decisive to maintain food production by farmers. These include improvements in productivity by means of agricultural technology, and output prices for farmers.

6.3. Limitations and future research avenues

The main objective of this thesis is to provide a comprehensive understanding of the dynamics of Vietnam agriculture and the changing conditions. Advanced technologies kept momentum for the dynamic adjustment of Vietnam agriculture. However, future sustainable development of Vietnam agriculture requires better technology development. Although the impacts of climate change seem not to be severe in the long term, Vietnam agriculture is expected to experience regionally and seasonally negative impacts resulted from changing temperatures and rainfalls. The findings of this thesis provide crucial implications for technology policy in the post-Green Revolution time as well as for adaptation strategy to cope with changing climate patterns. However, limitations are identified which generate avenues for future research.

First, Chapter 3 focused on technology change and its impacts on the rice sector. Rice has been the traditional crop which accounts for most of the annual cropping area in Vietnam. The transformation of Vietnam agriculture is also associated with changing crop production. A more comprehensive approach to technology change in agriculture is, therefore, important to understand the driving factor of technology diffusion and productivity improvements.

Second, the estimated impacts of climate on agricultural performance in Chapter 4, and on land use patterns in Chapter 5 did not take into account future changes in technology. Vietnam agriculture is undergoing transformation. Future technology advances may facilitate better adaptation by agriculture. Hence, the prediction of climate impacts on agricultural income and on land use may be overstated.

Finally, The Ricardian analysis in Chapter 4 implicitly measured the economic impacts of climate change given adaptation in terms of crop substitution. The estimated climate impacts are averaged across land use alternatives. It is, therefore, better to model the joint impacts of climate on land use change and on agricultural performance in a joint Ricardian framework. This will allow better understandings of the direct effects of climate change on crop production and the indirect effects on crop substitution.

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