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Thanh-Tung Nguyen, Trung Thanh Nguyen, Ulrike Grote

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Thailand Vietnam Socio Economic Panel (TVSEP)
TVSEP Database Centre
Leibniz Universität Hannover
Königsworther Platz 1
30167 Hannover, Germany

Contact: thanh.nguyen@iuw.uni-hannover.de

Weather Shocks, Credit and Production Efficiency of Rice Farmers in Vietnam

Thanh-Tung Nguyen[a,b*], Trung Thanh Nguyen[a], Ulrike Grote[a]

Abstract

Enhancement of rice production efficiency in developing countries is important to improve the livelihoods of farmers and to ensure global food security for a growing population. Despite significant progress in recent decades, rice production in these countries is facing multiple challenges from climate change, land degradation, to the increasing competition for land and labor from urbanization and industrialization. Given that rice farmers in Vietnam often suffer from extreme weather events and lack of access to credit, our study aims to (i) investigate the impact of weather shocks and credit on the rice production efficiency, and to (ii) examine the role of credit in mitigating the impact of weather shocks. We find that weather shocks, land fragmentation and the migration of household members are the major sources of inefficiency. Meanwhile, livestock, farm mechanization and education level are positive factors for rice production efficiency. In addition, our results show that access to credit plays a significant role in mitigating the negative impact of weather shocks. Our studies call for more assistance and support to farmers in mitigating the severe effect of weather shocks, in particular, via the promotion of credit market. In addition, the encouragement of farm mechanization, land defragmentation, livestock farming and the improvement of rural education should be given a high priority to improve the rice production efficiency.

Keywords: Weather shocks, Agricultural production efficiency, Credit

JEL: Q12, G50, Q54

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[a] Institute for Environmental Economics and World Trade, Leibniz Universität Hannover, Königsworther Platz 1, 30167 Hannover, Germany

[b] International School, Thai Nguyen University, 24000 Thai Nguyen, Vietnam

[*] Corresponding author, Tel.: +49 511 762 19567, Fax: +49 511 762 2667, E-mail: tung.nguyen@iuw.uni-hannover.de

1. Introduction

Rice is among the most important food crop in the world. It is estimated that more than half of the world's population depend on rice for more than 20% of their daily calorie intake and more than one billion people undertake rice production as their main livelihoods (FAO, 2014a). Although rice productivity has dramatically increased since the Green revolution, this growth is still insufficient to keep pace with the growth of the world population (FAO, 2014b). It is expected that our world still needs an additional 100 million tons of rice by 2035, equivalent to an annual yield increase of about two percent to feed the growing population (Seck et al., 2012). However, the growth in rice productivity has slowed considerably in recent decades, falling from two percent per year in the 1970s to less than one percent in the 2000s (IRRI et al., 2011). This slowdown could be explained by an increasing competition for land and labor from the urbanization and industrialization in developing countries (FAO, 2014b). In addition, land degradation due to the intensive use of chemical inputs, and the increasing intensity and frequency of extreme weather events due to global climate change are factors reinforcing this slowdown (FAO, 2014b).

Extreme weather events have been largely considered among the most severe threats to people all over the world. Over the last three decades, extreme weather events have resulted in around two million deaths and the economic losses of nearly four trillion US dollar (Eckstein et al., 2018). Extreme weather events severely undermine the growth in agricultural production, making the challenge of achieving food security, ending hunger, and promoting sustainable agriculture more difficult (FAO et al., 2018). Due to global climate change, extreme weather events are occurring more strongly, frequently and unexpectedly. Economic losses due to weather events dramatically increased from nearly 50 billion each year in the 1980s to around $200 billion each year in the last decade (World Bank, 2013). Although all nations are impacted, the impact of weather shocks appears to be more serve on households in low-income countries (Arouri et al., 2015; CRED & UNISDR, 2018). As social insurance mechanisms are limited, households in these countries are generally more vulnerable to weather shocks in both response and recovery phases. They are less likely to absorb damages and to recover from these disasters (see Arouri et al., 2015, Nguyen et al., 2020).

Credit is an important source of finance for agricultural production activities (Guirkinger & Boucher, 2008; Ali et al., 2014). It relieves farmers from financial capital constraints, therefore, allowing them to satisfy the demand for inputs, to adopt modern technologies, and to access markets. However, credit may have both positive and negative impacts on agricultural production. On the one hand, if it is used effectively, it could improve the agricultural production efficiency, promote the accumulation of physical and human capital, and enhance household living standards (see Liverpool & Winter-Nelson, 2010; Hermes & Lensink, 2011; Nguyen et al., 2019). In addition, it could improve households' resilience to shocks, promoting them to pursue productive farming methods (see Islam & Maitra, 2012; Isoto et al., 2017). On the other hand, the ineffective use of credit may push households into the situation of default or over-indebtedness, causing heavy stress and deteriorating their production processes (see World Bank, 2009; Seng, 2018). Furthermore, access to credit may promote young people to leave their agricultural lands and migrate to cities better employment opportunities (see Li et al., 2004; Swaminathan et al., 2010), causing the shortage of labor and the reduction of investment in agricultural production.

Vietnam is a developing country (Nguyen et al., 2019) with the economy highly depending on agricultural production. The agricultural sector accounts for around 40% of the employment, and 20% in the total gross domestic product (GDP) (World Bank, 2016). Rice is the most important food crop in Vietnam, contributing more than 40 per cent in the net production value of crops and occupying more than 40 per cent of agricultural land area (see World Bank, 2016; USAID, 2017). In recent decades, Vietnam has also achieved explosive growth in agricultural production, from a country once experienced hunger to become one of the top rice-exporting countries in the world. However, their productivity still lags behind peer regions and the growth in total factor productivity has considerably declined in recent years due to land degradation and the reduction in land, labor and public investment. In addition, rice production in Vietnam, which heavily rely on traditional technologies and weather conditions, are facing severe threats from global climate change. Located in the Southeast Asia region, Vietnam is among the top ten most vulnerable countries to climate risks. USAID (2017) reports that natural disasters caused nearly ten thousand fatalities and were responsible for losses equal to 1.5% of the annual GDP between 2001 and 2010. It is forecasted that the impact of climate change on Vietnam agriculture could result in the reduction of around two per cent of total GDP in 2050 (USAID, 2017; Trinh, 2018).

Our study has three main objectives. First, our study aims to investigate the impact of weather shocks and credit on the production efficiency of rice farmers in Vietnam. Secondly, we examine whether credit plays a role in mitigating the impact of weather shocks on farmers' production efficiency. This study contributes to the current literature in some important aspects. First, although the effects of weather shocks on rice yield were investigated (see Ali et al., 2014; Guirkinger & Boucher, 2008; Isoto et al., 2017), the linkages between weather shocks and rice production efficiency have been paid little attention. High yields do not necessarily mean high efficiency because farmers could increase their yields by using more inputs, but not efficiently utilize inputs (Yang et al., 2016). The practices of increasing rice productivity via over-intensive use of fertilizer and other chemical inputs could result in environmental costs of land degradation and water pollution, potentially damaging the sustainability of agricultural production. Meanwhile, the enhancement of farm production efficiency is defined as the increase of household capability to maximize total outputs with a given amount of inputs. Second, our study is the first effort to examine the role of credit in mitigating the effects of weather shocks on rice production efficiency. Although previous studies demonstrated that households tend to use credit in response to shocks, no empirical studies have been taken to measure the effects of credit in mitigating the impacts of weather shocks on agricultural efficiency. Last, as credit and weather shocks are potentially correlated with other household characteristics, failure to control unobserved characteristics may result in biased estimates of production efficiency. This problem is not well addressed in the existing literature. Therefore, we extend our one-step stochastic frontier models with Mundlak approach (also called correlated random-effects approach) (see Mundlak, 1978; Yang et al., 2016), to control for unobserved households characteristics as determinants of production inefficiency.

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

2. Theoretical Framework

2.1. Farm Production Efficiency

Efficiency is a basic notion in economics. It interrelates inputs and outputs of production activities. Farm production efficiency can be determined with either input- or output orientations. The output-oriented efficiency measurement evaluates the capability of farmers to maximize their output with a given amount of inputs, meanwhile the input-oriented efficiency measurement evaluates the capacity to minimize the input use for a specific amount of outputs. For the purpose of our study, the output-oriented model is selected as the theoretical framework. Based on the output-oriented model, a farm is fully production efficient if it could not increase its value of output without increasing their inputs expenditure. Production efficiency is measured as the ratio of the observed value of output to the value of output of a fully efficient farm (Farrell, 1957; Ebers et al., 2017). As the production function of the fully efficient farm is unknown, it has to be estimated (Battese & Coelli, 1995; Ebers et al., 2017). In the literature, the production efficiency could be estimated either with the non-parametric approach of Data Envelopment Analysis (DEA) or with the parametric approach of Stochastic Frontier Model (SFM). However, the DEA approach does not take into account of measurement errors and other sources of statistical noise, therefore, SFM is more favoured in analysing the farm production efficiency (see Hardaker et al., 2004; Coelli et al., 2005; Nguyen et al., 2018). The SFM is specified as follows:

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

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

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

The measure of farm production efficiency range from zero to one. The value of zero indicates that the farm is fully inefficient, meanwhile the value of one implies that the farm is fully efficient.

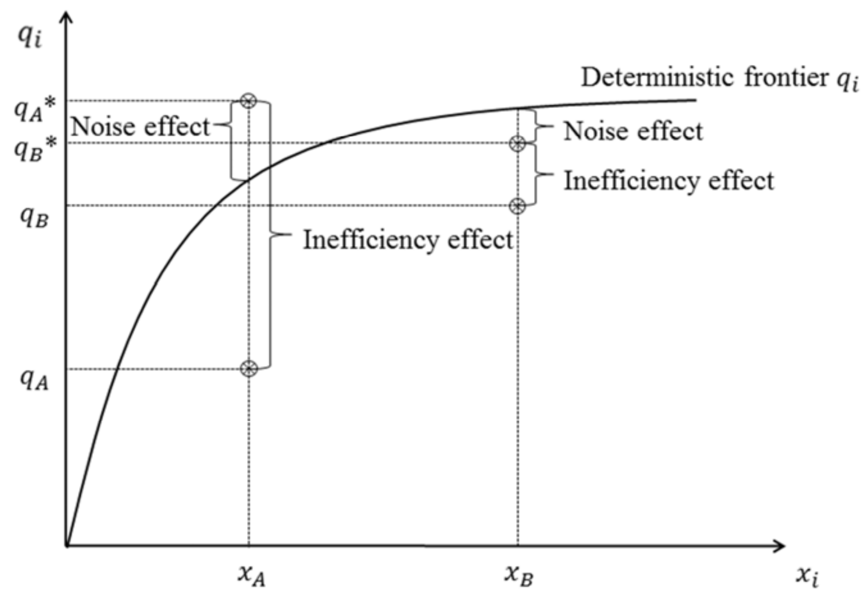

Figure 1. The Stochastic Production Frontier (Source: Coelli et al., 2005; Ebers et al., 2017)

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

2.2. Sustainable Livelihood Framework

Our study extends the Sustainable Livelihoods Framework (see Scoones, 1998; Nguyen et al., 2015) to analyse the impact of weather shocks, credit and other factors on the production efficiency. In this framework, a household is considered as the basic decision-making unit. Household livelihood framework consists of three main components: livelihood assets, livelihood activities and livelihood outcomes. Livelihood assets include human capital (e.g. age, education, and household size), financial capital (e.g. credit, remittance), natural capital (e.g. agricultural land, land fragmentation), physical capital (e.g. machinery, livestock, motorbike) and social capital (e.g. ethnicity, phones). Based on these assets, households may choose a livelihood portfolio of different activities such as farm, non-farm employment or migration. The combination of livelihood assets and livelihood activities leads to livelihood outcomes, such as farm production efficiency, income and consumption. In addition, household livelihood is affected by external factors such as extreme weather events and macro socio-economic factors. The magnitude of the impact of shocks on household's livelihood depends on household resilience capacity. Resilience is defined as the capacity of households to mitigate shock's damage and the ability to recover from shocks. Exposed to the same disasters, households with low resilience capacity suffer more damage than those with high resilience capacity (Arouri et al., 2015).

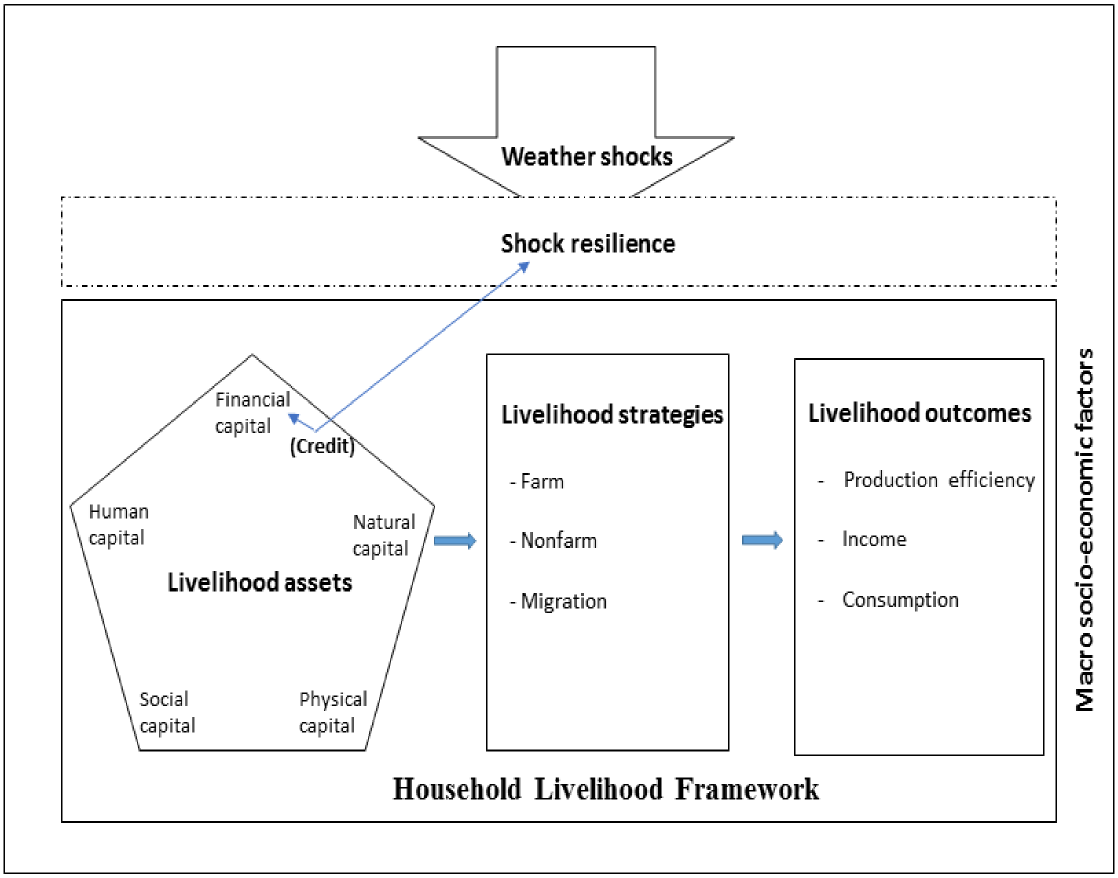

Figure 2. Sustainable Livelihood Framework (Source: Modified from Scoones, 1998; Nguyen et al., 2015)

In this framework, weather shocks are expected to negatively affect the production efficiency of rice farmers as these events not only cause crop losses but also increase household's expenditure for planting, growing and caring crop. With respect to access to credit, its impacts on production efficiency may occur via two main channels. In the first channel, as an important livelihood asset, credit could affect the selection, the combination and the outcomes of livelihood activities as well as other household capital. For example, access to credit allows households to satisfy their input demands, to mechanize farming activities, to purchase high-yield seeds, consequently, enhancing their production efficiency. In the second channel, credit could affect the production efficiency of farmers via its impacts on household resilience capacity. Households with access to credit could have a better preparation to cope with extreme weather events, for example, by investing more in irrigations and drainage system. They also have a higher ability to ensure the continuity of the production process and to recover from weather extreme events (e.g. via satisfying the urgent demands for labor, irrigation, fertilizer or other inputs). In addition, they may not need to use shock-coping strategies which is harmful to agricultural production (e.g., selling productive farm asset, agricultural land).

3. Data Sources and Analysis

3.1. Data Sources

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

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

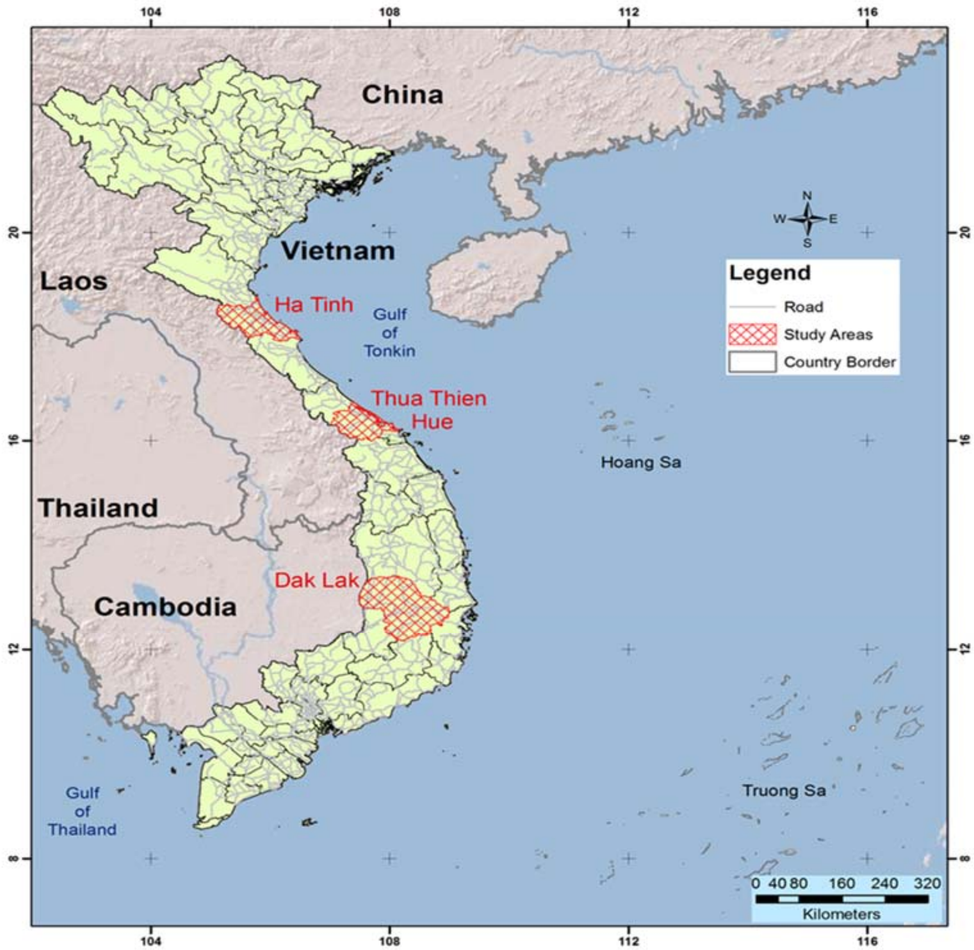

Figure 3. Map of surveyed provinces in Vietnam

The data collection follows a three-stage cluster sampling procedure (see Hardeweg et al., 2012; Do et al., 2019). The first stage is the selection of surveyed sub-district within provinces. Because the size of the commune population is not available at the time of sampling, the population share of respective districts is used to select sampled sub-district. At the second stage, 220 villages were sampled with probability proportional to the size of the village's population. At the last stage, 10 households in each sampled village were randomly chosen from a list of households with equal probability selection. For the purpose of our study, which focuses on the rice production efficiency, we restrict our sample to households which have harvested rice land in the surveyed period and are observed in all three waves of 2010, 2013 and 2016. Finally, our sample includes 3000 observations of 1000 households.

A household questionnaire is used to collect detailed information on the background of household individuals (age, household size, ethnicity, education, and health), household livelihood activities (farming, livestock rearing, hunting, non-farm employment), credit, investment, asset and expenditure. In particular, the shock section includes information on types of shock events, time of occurrence, severity, and losses. Regarding the borrow section, detailed information on the value, source, time, and duration of loans is collected. The farm section captures information on crop varieties, planted area, total output, sale price, and expenditure for land preparation, for seed and seedlings, fertilizer, pesticides, weeding, harvesting and irrigation.

3.2. Data Analysis

3.2.1 Stochastic Frontier Analysis

There are two main approaches in the literature of production efficiency analysis using stochastic frontier model, namely two-step stochastic frontier model and one-step stochastic frontier model (Nguyen et al., 2012; Yang et al., 2016). In the former approach, the production efficiency score for each farmer is estimated after the stochastic frontier production function is estimated. Then, the estimated production efficiency score is regressed on variables which potentially determine the farm production efficiency. However, this approach is commonly criticized as it may give biased results (Ebers et al., 2017; Wang & Schmidt, 2012). This problem results from the uncontrolled correlation between household characteristics and farm input characteristics. In addition, even if this correlation does not exist, biased estimate of inefficiency score may also result from the misspecification of the first step which ignore the impact of household characteristics on inefficiency. This problem is similar to omitted variable problems in the linear regression (Yang et al., 2016). Therefore, our study adopts the latter approach, namely one-step stochastic frontier model. This approach could deal with the limitation of the former approach by simultaneously estimate the stochastic frontier production function and the production inefficiency function.

A problem in estimating the impacts credit and weather shocks is their potential endogeneity (see Arouri et al., 2015; Kislat, 2015). In other words, these variables are likely correlated to unobservable household characteristics and failure to control for these unobservable variables potentially lead to biased results. Therefore, we follow Yang et al. (2016) to include the time average of potentially endogenous variables to control for unobserved households characteristics as determinants of the production inefficiency. In addition, as we have panel data, our estimations are conducted by True Random Effect approach[2] (TRE) (Greene, 2005), an extension of the standard random-effect approach of Pitt and Lee (1981) to separate the sources of time-invariant heterogeneity and the inefficiency component. As the likelihood-ratio test shows that the Translog function form is more appropriate than Cobb-Douglas function form (see Appendix A2), our model is specified as follows:

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

with

$$U_{it} = \beta_0 + \beta_1 C_{it} + \beta_2 W_{it} + \beta_3 H_{it} + \beta_4 P_{it} + \beta_5 Y_i + \beta_6 \bar{C_i} + \beta_7 \overline{W}_i + \beta_8 \overline{H}_i + \epsilon_{it} \qquad (4)$$

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

where Y_{it} is the total value of rice output of household i at time t. I_{it} is the vector of inputs. The inputs variables are land[3], land preparation cost, irrigation cost, fertilizer cost, pesticide cost, seed and seedling cost, harvesting cost, other input costs, and the number of household labour working on their own farm[4]. In our model, monetary variables are converted to 2005 PPP US dollar. ω_i denotes farm-specific and time-invariant heterogeneity. V_{it} is the error term to capture noise effects. U_{it} is the production inefficiency term and is regressed on a set of variables including household livelihood assets, livelihood activities, year, province and time average of potentially endogenous variables. In particular, C_{it} is a dummy variable indicating whether household i at time t access to credit or not. In addition, we also estimate our models with dummy variables of access to informal credit and access to formal credit[5]. W is a dummy variable indicating whether the household is affected by a weather shock. H is the vector of household livelihood assets, livelihood activities. This includes household's human capital (age of household head, education of household head, household size, share of children members), physical capital (number of tractors, the value of livestock, number of motorbikes), social capital (ethnicity, number of phones), financial capital (the value of received remittance from friends, relatives and migrant members), natural capital (owned agricultural land, agricultural land fragmentation), livelihood activities (migration, non-farm employment). P and Y are province and year dummy variables, respectively. $\bar{C}, \overline{W}, \bar{H}$ are the time average of C, W and H, respectively. These variables are used to control unobserved variables and the sign of these variables do not have meaningful interpretations (Yang et al., 2016; Gautam & Ahmed, 2018). For household head characteristic variables such as ethnicity and education, we do not include the time average of these variables because these variables are likely exogenous and their value

[3] Rice land and input expenditures are only accounted for rice cultivated plots which has already been harvested in the surveyed years

[5] We do not disaggregate informal credit into sources from money lenders and from relatives because the share of sampled households borrowing from money lender source is quite small, only around 5%.

are almost unchanged during surveyed years. All inputs variables in Equation 3 are normalized by dividing every variable observation by its respective sample mean before estimation, then the coefficients on the first order term can be read directly as elasticities at means (see Yang et al., 2016; Holtkamp & Brümmer, 2017). The detailed information of explanatory variables are given in Appendix A1.

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

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

The sign of θ_1 indicates the impact of credit on the production inefficiency of farmers who are not affected by weather shocks. The sum of θ_1 and θ_2 indicates the impact of credit on farmers who are affected by weather shocks. The sign of θ_2 indicates the impact of weather shocks on farmers who are not access to credit. The sum of θ_2 and θ_3 indicates the impact of weather shocks on farmers who have access to credit. If $\theta_3 > 0$ and θ_2>0, then $(\theta_2 + \theta_3) > \theta_3 > 0$, this indicates weather shocks have positive impacts on production inefficiency in both groups of households with or without credit. In other words, weather shocks negatively affect production efficiency and this effect is more severe in the groups of households with access to credit than the other. If $\theta_3 > 0$, but θ_2<0, then$(\theta_3 + \theta_2) < \theta_3$. This indicates the negative impact of weather shocks on the production efficiency is more severe in the group of households without credit access to credit. In other words, it shows that access to credit has a significant role in mitigating the negative impact of weather shocks on production efficiency. In addition, we also conduct hypothesis tests of our stochastic models including the choice of frontier production function form, whether the efficiency is stochastic and whether the efficiency is presented in our models. These results significantly support our models. Furthermore, we also undertake robustness checks. In particular, we estimate our models with the quantity of output (in tons) replacing the value of total output (in PPP$) in Equation 1. In addition, our models are estimated with Cobb-Douglas production function. These results are highly consistent with our findings (see Appendix A3 and A4).

4. Results and Discussion

Table 1 summarizes households' characteristics by exposure to weather shocks. For human capital, non-affected households appear to have a higher level of education, a lower share of children, and smaller household size. Regarding social capital, non-affected households also have more mobile phones. The share of ethnic minority households, who are typically featured by a lower living condition, in the non-affected group is also lower than in the affected group. Regarding physical capital, non-affected households appear to have more motorbike than affected households. With regard to financial capital and natural capital, non-affected households appear to have a higher value of received remittances than affected households. However, affected households appear to have larger agricultural land and they are also more likely to borrow, particularly from informal sources than non-affected households. In term of household livelihood strategies, non-affected households are more likely to occupy in nonfarm sectors or to migrate than affected households.

Table 1. Household characteristics

	whole sample	households affected by weather shocks	non-affected households
access to credit (%)	49.90	47.86***[a]	54.52*** [a]
access to formal credit (%)	32.30	31.81	33.41
access to informal credit (%)	25.50	23.40*** [a]	30.25*** [a]
remittance (PPP $)	1,061	1,196*** [b]	753*** [b]
household size (people)	4.20	4.10*** [b]	4.42*** [b]
child share (%)	19.66	18.71*** [a]	21.82*** [a]
age head (years)	51.59	52.41*** [b]	49.73*** [b]
school head (years)	6.81	6.98*** [b]	6.44*** [b]
ethnic minority (%)	21.87	15.57*** [a]	36.13*** [a]
phone (numbers)	1.95	2.06*** [b]	1.71*** [b]
tractor (numbers)	0.39	0.39	0.41
livestock (PPP $)	1,840	1,802	1,926
motorbike (numbers)	1.20	1.24*** [b]	1.11*** [b]
owned farm land (ha)	0.62	0.54*** [b]	0.79*** [b]
farm land fragmentation (plots)	0.11	0.12	0.10
migration (%)	47.30	48.58** [a]	44.40** [a]
non-farm employment (%)	43.43	47.14***[a]	35.04*** [a]
No. of observations	3000	2081	919

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

Table 2 reports farm input-output characteristics. Generally, farmers spend the highest expenditure on fertilizer. This amount is above 400 PPP $ per ha, more than twice as high as the second and the third highest, which are the expenditure for harvesting and land preparation, respectively. This is consistent with World Bank (2016) which also reports that Vietnam agriculture has been featured by the intensive use of fertilizer. Fertilizer is the highest single cost-item in rice production with the application rates per ha about 30-200% higher than other Southeast Asian countries (World Bank, 2016). Comparing between households who are affected by weather shocks and non-affected households, affected farmers appear to have less crop land than non-affected farmers, but they spend more on input expenditure such as fertilizer, pesticide and seed. Non-affected farmers also have higher total output value, but no significant differences in the rice yield between these two groups. These figures are reasonable as farmers may partially offset damages of extreme weather events to their crop yield by spending more on fertilizer, pesticide and seed.

Table 2. Farm input-output characteristics

	whole sample	households affected by weather shocks	non-affected households
fertilizer cost (PPP $ per ha)	438.36	420.79***	478.15***
pesticide cost (PPP $ per ha)	106.21	103.43**	112.52**
harvesting cost (PPP $ per ha)	198.75	187.92	223.26
land preparation cost (PPP $ per ha)	178.11	175.10	184.92
seed cost (PPP $ per ha)	125.56	116.13***	146.92***
other cost (PPP $ per ha)	64.60	63.12	67.93
labor (labor per ha)	6.80	6.10***	8.37***
rice land (ha)	0.55	0.57***	0.52***
rice output (PPP $)	1,530	1,615**	1,340**
rice yield (PPP $ per ha)	2,797	2,818	2,749
No. of observations	3000	2081	919

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

The estimation of the stochastic frontier production function is given in Table 3. The results show that total rice output value is positive and significant correlated with almost input variables, except the expenditure on land preparation. The production elasticity of cropland is the highest (0.68), followed by that of fertilizer (0.13). This result is also consistent with Kompas et al. (2012), showing that land and fertilizer are the most important inputs in rice production in Vietnam. World Bank (2016) also reports that the success in Vietnam's agricultural growth in recent decades has come from the intensive use of land, and relatively heavy use of fertilizer. However, this practice may not be promoted because it potentially causes severe environmental consequences such as land degradation and pollution (World Bank, 2016). In addition, our findings shows that the expenditure on harvesting is the third important input with its elasticity around 0.07. Harvesting is the process of collecting the mature rice crop, including activities of reaping, stacking, handling, threshing, cleaning, and hauling. A good harvesting method is important to minimize crop losses and quality deterioration (IRRI, 2019). Furthermore, our results indicate that the number of labor and expenditure on pesticide, seed and other inputs (including irrigation and weeding) also significantly contribute to the total output value.

The overall production efficiency score and distribution of production efficiency are shown in Figure 4. The value of zero indicates that farmers are fully inefficient, meanwhile the value of one imply that farmers are fully efficient. The mean of estimated production efficiency score is 0.79, highly consistent with Kompas et al. (2012) and Pedroso et al. (2018). Most of the sampled households (70%) have efficiency scores from 0.7 to 0.9. Around 10% of households have efficiency higher than 0.9, while less than five percent of households have efficiency scores less than 0.5. This indicates that in general, Vietnamese rice farmers are relatively efficient in their production, but on average, they are just producing at around 80% of their maximum capacity. With existing technology and input resources, they can improve their production output by about 20%.

Table 3. Maximum-likelihood estimates of the stochastic production frontier function

Translog Stochastic Frontier Production		
	Coefficient	Robust Std. Err.
ln rice land	0.684***	(0.032)
ln fertilizer cost	0.127***	(0.019)
ln pesticide cost	0.035***	(0.013)
ln harvesting cost	0.066***	(0.018)
ln land preparation cost	-0.013	(0.014)
ln seed cost	0.036***	(0.014)
ln other costs	0.053***	(0.010)
ln labor	0.044**	(0.020)
$(\ln \text{rice land})^2$	0.012***	(0.002)
$(\ln \text{fertilizer cost})^2$	0.004***	(0.002)
$(\ln \text{pesticide cost})^2$	-0.002	(0.001)
$(\ln \text{harvesting cost})^2$	0.003**	(0.002)
$(\ln \text{land preparation cost})^2$	0.011	(0.028)
$(\ln \text{seed cost})^2$	0.007***	(0.002)
$(\ln \text{other costs})^2$	0.006***	(0.001)
$(\ln \text{labor})^2$	0.007**	(0.003)
ln rice land * ln fertilizer cost	0.001	(0.001)
ln rice land * ln pesticide cost	0.000	(0.000)
ln rice land * ln harvesting cost	-0.000	(0.001)
ln rice land * ln land preparation cost	-0.011*	(0.006)
ln rice land * ln seed cost	-0.001	(0.001)
ln rice land * ln other costs	0.000	(0.001)
ln rice land * ln labor	0.002	(0.002)
ln fertilizer cost * ln pesticide cost	0.000	(0.000)
ln fertilizer cost * ln harvesting cost	-0.000	(0.000)
ln fertilizer cost * ln land preparation cost	-0.002	(0.002)
ln fertilizer cost * ln seed cost	-0.001***	(0.000)
ln fertilizer cost * ln other costs	-0.000*	(0.000)
ln fertilizer cost * ln labor	-0.001*	(0.000)
ln pesticide cost * ln harvesting cost	-0.000	(0.001)
ln pesticide cost * ln land preparation cost	-0.002	(0.002)
ln pesticide cost * ln seed cost	0.000	(0.000)
ln pesticide cost * ln other costs	0.000	(0.000)
ln pesticide cost * ln labor	-0.001	(0.001)
ln harvesting cost * ln land preparation cost	0.008	(0.006)
ln harvesting cost * ln seed costs	0.001*	(0.001)
ln harvesting cost * ln other costs	-0.000	(0.001)
ln harvesting cost * ln labor	-0.000	(0.003)
ln land preparation cost * ln seed cost	0.005*	(0.002)
ln land preparation cost * ln other costs	-0.003	(0.002)
ln land preparation cost * ln labor	-0.004	(0.005)
ln seed cost * ln other costs	-0.000	(0.000)
ln seed cost * ln labor	-0.000	(0.002)
ln other cost * ln labor	-0.000	(0.001)
Constant	7.523***	(0.023)
No. of observations	3000	
Prob. > Chi^2	0.0000	
Log simulated-likelihood	-1565.0266	
Test constant return to scale (p-value)	0.238	

*Robust standard errors clustered at village level in parentheses; *** p<0.01, ** p<0.05, * p<0.1; this model is simultaneous estimated with the full inefficiency function, including informal, formal credit and their interaction with credit and other explanatory variable reported in table 4; as inputs variables are normalized by their respective means, coefficients on the first order term can be read directly as elasticities at means*

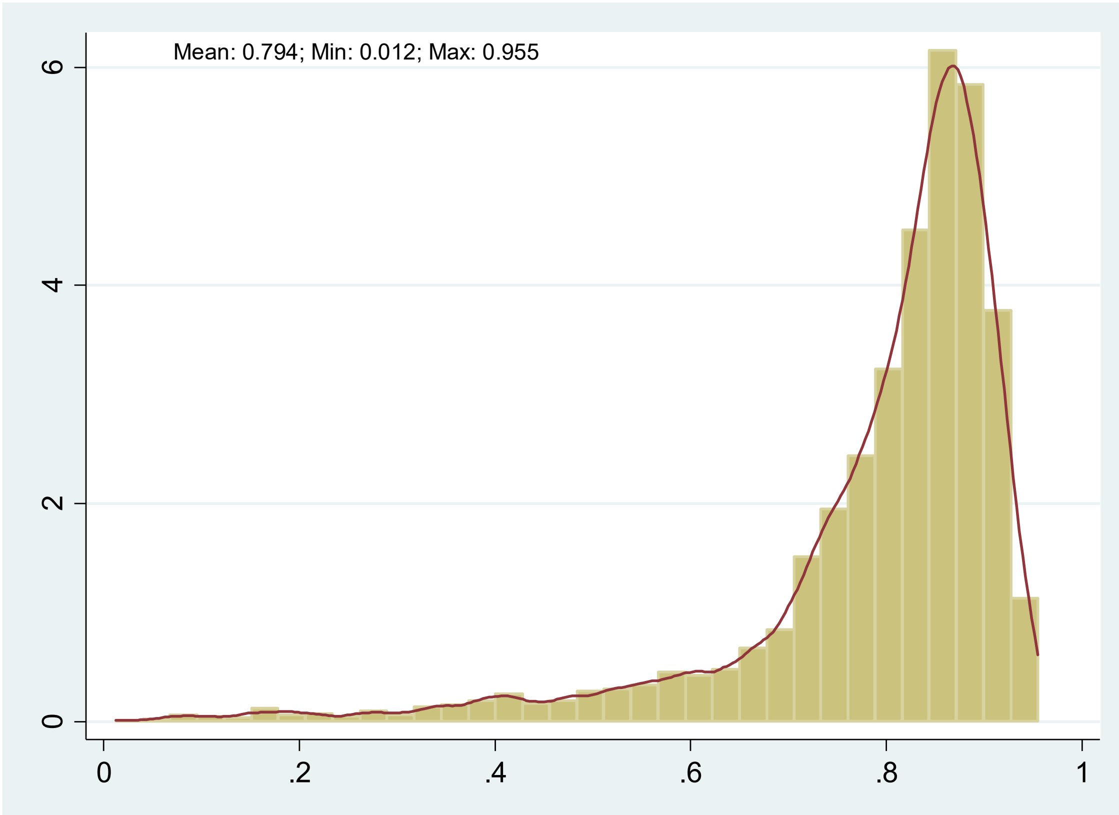

Figure 4. Estimated production efficiency scores and distribution

Table 4. Maximum-likelihood estimates of the inefficiency function

	(1)	(2)	(3)	(4)
weather shock*informal credit				-0.803***
weather shock*formal credit				0.181
weather shock*credit			-0.539*	
informal credit		-0.062		0.202
formal credit		0.001		-0.044
credit	-0.030		0.167	
weather shock	0.560***	0.563***	0.831***	0.714***
remittance	-0.000	-0.000	-0.000	-0.000
household size	0.061	0.062	0.052	0.057
child share	0.612	0.632	0.616	0.548
age head	0.001	0.001	0.001	0.001
school head	-0.044**	-0.043**	-0.045**	-0.046**
ethnic minority	1.302***	1.328***	1.305***	1.372***
phone	-0.038	-0.038	-0.045	-0.044
tractor	-0.188*	-0.188*	-0.195*	-0.187*
livestock	-0.000**	-0.000**	-0.000**	-0.000**
motorbike	0.013	0.018	0.034	0.047
owned farm land	0.123	0.137	0.123	0.132
farm land fragmentation	0.327***	0.326***	0.331***	0.360***
migration	0.282*	0.288*	0.264*	0.283*
non-farm employment	0.115	0.115	0.136	0.144
2010	-0.593***	-0.593***	-0.592***	-0.595***
2013	-0.129	-0.116	-0.139	-0.144
Hatinh	1.062**	1.079**	1.055**	1.103**
Hue	0.915***	0.968***	0.891***	0.957***
weather shock (time average)	0.086	0.079	0.104	0.117
credit (time average)	0.661**		0.652**	
informal credit (time average)		0.617*		0.688*
formal credit (time average)		0.730***		0.686***
remittance (time average)	0.000	0.000	0.000	0.000
household size (time average)	-0.033	-0.036	-0.024	-0.038
child share (time average)	-0.764	-0.761	-0.747	-0.683
phone (time average)	-0.086	-0.099	-0.069	-0.092
farm machinery (time average)	0.496*	0.475	0.488	0.462
livestock (time average)	0.000	0.000	0.000	0.000
motorbike (time average)	-0.463**	-0.467**	-0.479**	-0.489**
owned farm land (time average)	-0.037	-0.051	-0.051	-0.060
farm land fragmentation (time average)	-0.693	-0.659	-0.724	-0.704
migration (time average)	0.016	-0.012	0.030	0.006
non-farm employment (time average)	-0.166	-0.168	-0.184	-0.179
Constant	-3.414***	-3.532***	-3.525***	-3.571***
No. of observations	3000	3000	3000	3000
Prob. > Chi^2	0.000	0.000	0.000	0.000
Log simulated-likelihood	-1574.064	-1569.940	-1571.3261	-1565.027

*Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; the production inefficiency functions are simultaneously estimated with the translog stochastic frontier production function; time-average variables to control for unobserved households characteristics, but their sign do not have meaningful interpretations.*

Table 4 reports the estimation of the determinants of production inefficiency. In particular, columns 1 and 2 show the results for our first research question of to what extent weather shocks and credit affect the production efficiency of rice farmers. In column 3 and 4, we include interactions between weather shocks and credit sources to examine the role of credit in mitigating the effect of weather shocks.

Column 1 and 2 show that weather shocks are positively and significantly correlated with the production inefficiency of rice farmers. This indicates weather shocks severely deteriorate the production efficiency of rice farmers. This is consistent with our expectation that weather shocks not only cause crop losses but also increase household's expenditure for planting, growing and caring crop, therefore worsening the production efficiency of rice farmers. This is consistent with Mishra et al. (2015), Mishra et al. (2018) and Pedroso et al., (2018), who found that weather extreme events are major sources of production inefficiency in rice production. Regarding access to credit, we do not have sufficiently statistical evidence to conclude this impact on farm production efficiency. For other household characteristics, regarding human capital, households with a higher education level tend to be more efficient in farming activities. This is reasonable because farmers with higher education level are more able to manage information related to markets, climate, environment, production system and technologies (Ebers et al., 2017; Nguyen et al., 2018). With regard to physical capital, the number of tractors, representing the level of farm mechanization, is negatively associated with farmers' production inefficiency. FAO and World Bank (2009) argue that farm mechanization will improve significantly agricultural productivity by facilitating timeliness and quality of cultivation, relieving the burden of labor shortages, and reducing harvest losses and expense for land preparation and harvesting operations. In addition, our findings show the value of livestock is negatively correlated with farm production efficiency. It is reasonable because the waste from livestock is an important source of fertilizer for crop land. In addition, rice farming activities in developing countries still highly rely on draught animal power. In term of natural capital, the impact of land fragmentation positively affect farmers' production inefficiency. It makes sense as land fragmentation increase production costs and discourages farmers from adopting innovations and modern technologies (Rahman & Rahman, 2009; Di Falco et al., 2010). This finding is consistent with Pedroso et al. (2018) and Huy and Nguyen (2019), showing that land fragmentation is a major source of farming production inefficiency in Vietnam. In term of social capital, ethnic minority households appear to have a lower production efficiency than ethnic majority households. This is consistent with van de Walle and Gunewardena (2001) and Baulch et al. (2012), who report that the ethnic minority in Vietnam generally has a lower return to productive assets than the ethnic majority. Regarding livelihood strategies, the migration of household members significantly deteriorates the production efficiency. This makes sense as the shortage of household labor may cause detrimental effects on the efficiency of farming activities (Sauer et al, 2015).

To examine whether credit plays a significant role in mitigating the effect of weather shocks, we include the interaction between credit and weather shocks in column 3. This interaction is negatively correlated with the production inefficiency, implying the significant role of credit in mitigating the effect of weather shocks. In column 5, we also disaggregate credit into formal and informal credit. The results show that the interaction between informal credit and weather shocks is significant and negative, meanwhile the interaction between formal credit and weather shocks is insignificant. In Appendix 5, we also use a simultaneous probit model to analyze the determinants of factors affecting households' access to credit sources and find that household tend to access to informal credit in response to weather shocks. This make senses because formal credit generally requires complicated application procedure and high collateral ratio, meanwhile informal credit may be easier to access and available on short notice (see Barslund and Tarp, 2008). Therefore, informal credit is more suitable for urgent purposes such as response to shocks than formal loans. Becchetti and Castriota (2011) argue that households in developing countries generally lack self-insurance instruments such as savings and accumulated assets, therefore borrowing is an important recovery instrument against natural catastrophes. Arouri et al. (2015) also claim that households with access to credit are more resilient to extreme weather events. Access to credit relieves households of financial capital constraints, allow them to invest more in their infrastructure, therefore, when extreme weather events occur, their losses could be significantly mitigated. This also helps households to ensure the continuity of the production process and to recover from faster from shocks by satisfying their urgent demands for irrigation, labor, fertilizer or other inputs. In addition, with access to credit, they may less likely to use shock-coping strategies which is harmful to their agricultural production such as depleting productive asset or selling agricultural land (Isoto et al., 2017)

Table 5. Estimated production efficiency scores by groups

	weather shock non-affected households		weather shock affected households	
	Mean	Std. Dev	Mean	Std. Dev
without informal credit	0.821***	0.124	0.747***	0.164
with informal credit	0.784	0.136	0.770	0.139
without formal credit	0.815***	0.127	0.756***	0.161
with formal credit	0.807***	0.129	0.750***	0.150
Whole sample	0.812***	0.128	0.754***	0.157
No. of observations	2081		919	

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

Figure 5 compares the production efficiency scores between affected households and non-affected households. In the whole sample, farmers who suffer from weather shocks generally have an average production efficiency score of 0.76, significantly lower than the figure of 0.81 of non-affected households. We also disaggregate our sample into subsamples of those with access to formal credit, without access to formal credit, with access to informal credit, and without access to informal credit. The results show that non-affected households are more significantly efficient than affected households in sub-samples of households with access to formal credit, without access to formal credit and without access to informal credit. Only in the group of households with access to informal credit, there is no significant difference in the production efficient score between affected households and non-affected households. This confirms the important role of informal credit in mitigating the impact of shocks on the production efficiency of rice farmers.

5. Conclusion

This study use a three-year balanced panel dataset of 1000 rice farmers collected in rural Vietnam in 2010, 2013 and 2016 to (i) investigate the impact of weather shocks and credit on production efficiency of rice farmer in Vietnam, to (ii) examine whether credit plays a role in mitigating the impact of weather shocks on rice production efficiency. This study contributes to the economics literature in some important aspects. Firstly, although a number of studies has investigated the effect of weather shocks and of credit on rice yield, limited studies have focused on these impacts on rice production efficiency. Second, our study is the first effort to examine the role of credit in mitigating the effects of weather shocks on rice production efficiency. Lastly, in our one-step stochastic frontier model, we adopt Mundlak approach to dealt with endogeneity problems which caused by potentially endogenous variables (e.g. credit and weather shocks) in the estimation of the production efficiency. Based on our knowledge, this problem is not well addressed in the previous studies which measure the impact of credit or weather shocks on farm production efficiency.

Our results reveal that the mean production efficiency score of sampled farmers is 0.79, representing a significant gap (21%) between frontier and actual rice farmers. This indicates that farmers could significantly increase their total output value with existing technology and resources. In addition, our findings show that weather shocks are major sources of production inefficiency. Our results also show that access to credit, particularly, access to informal credit, has a significant role in mitigating the negative impact of weather shocks on production efficiency. Furthermore, our findings show that rice production efficiency is significantly affected by various factors representing household's livelihood assets and livelihood activities. In term of human capital, households with higher education level tend to be more efficient in farming activities. Regarding households' physical capital, tractors and livestock are positively correlated with farmers' production efficiency. In term of natural capital, land fragmentation is found to have detrimental effects on the production efficiency. With regard to social capital, ethnic minority households appear to have lower production efficiency than ethnic majority households. For household's livelihood activities, the migration of household members is found to significantly deteriorate the production efficiency of farmers.

Our results also provide several important implications to the government and policymakers. Firstly, the government has to provide more assistance and support to farmers in mitigating the severe effect of weather shocks. In particular, the promotion of credit market, especially the informal credit market, should be an important instrument to mitigate these negative impacts. In addition, the combination of farming and livestock rearing is suggested to enhance the rice-farming production efficiency. Promoting farm mechanization, land defragmentation and rural education should be also given a high priority. Furthermore, Vietnamese government should have more assistance programs to support ethnic minority farmers to improve their production efficiency. In addition, policymakers should take into account the negative impact of migration on agricultural production in rural areas.

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Appendices

Appendix 1. Name and definition of explanatory variables

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

Appendix 2. Hypothesis test for stochastic frontier model

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

$L(\widehat{\Omega}_{H0})$ is the log likelihood of constrained models under the null hypothesis, and $L(\widehat{\Omega}_{H1})$ is the log likelihood of the alternative hypothesis in Table 4; p-value is taken from Kodde and Palm (1986).

Appendix A3. Maximum-likelihood estimates of the inefficiency function (simultaneously estimated with Translog Frontier Production Function in which total rice output (in tons) is the main outcome)

	(1)	(2)	(3)	(4)
weather shock*informal credit				-0.803***
weather shock*formal credit				0.181
weather shock*credit			-0.539*	
informal credit		-0.062		0.202
formal credit		0.001		-0.044
credit	-0.030		0.167	
weather shock	0.560***	0.563***	0.831***	0.714***
remittance	-0.000	-0.000	-0.000	-0.000
household size	0.061	0.062	0.052	0.057
child share	0.612	0.632	0.616	0.548
age head	0.001	0.001	0.001	0.001
school head	-0.044**	-0.043**	-0.045**	-0.046**
ethnic minority	1.302***	1.328***	1.305***	1.372***
phone	-0.038	-0.038	-0.045	-0.044
tractor	-0.188*	-0.188*	-0.195*	-0.187*
livestock	-0.000**	-0.000**	-0.000**	-0.000**
motorbike	0.013	0.018	0.034	0.047
owned farm land	0.123	0.137	0.123	0.132
farm land fragmentation	0.327***	0.326***	0.331***	0.360***
migration	0.282*	0.288*	0.264*	0.283*
non-farm employment	0.115	0.115	0.136	0.144
2010	-0.593***	-0.593***	-0.592***	-0.595***
2013	-0.129	-0.116	-0.139	-0.144
Hatinh	1.062**	1.079**	1.055**	1.103**
Hue	0.915***	0.968***	0.891***	0.957***
weather shock (time average)	0.086	0.079	0.104	0.117
credit (time average)	0.661**		0.652**	
informal credit (time average)		0.617*		0.688*
formal credit (time average)		0.730***		0.686***
remittance (time average)	0.000	0.000	0.000	0.000
household size (time average)	-0.033	-0.036	-0.024	-0.038
child share (time average)	-0.764	-0.761	-0.747	-0.683
phone (time average)	-0.086	-0.099	-0.069	-0.092
farm machinery (time average)	0.496*	0.475	0.488	0.462
livestock (time average)	0.000	0.000	0.000	0.000
motorbike (time average)	-0.463**	-0.467**	-0.479**	-0.489**
owned farm land (time average)	-0.037	-0.051	-0.051	-0.060
farm land fragmentation (time average)	-0.693	-0.659	-0.724	-0.704
migration (time average)	0.016	-0.012	0.030	0.006
non-farm employment (time average)	-0.166	-0.168	-0.184	-0.179
Constant	-3.414***	-3.532***	-3.525***	-3.571***
No. of observations	3000	3000	3000	3000
Prob. > Chi^2	0.000	0.000	0.00	0.000

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

Appendix A4. Maximum-likelihood estimates of the inefficiency function (simultaneously estimated with Cobb-Douglas Frontier Production Function)

	(1)	(2)	(3)	(4)
weather shock*informal credit				-0.715***
weather shock*formal credit				0.165
weather shock*credit			-0.474*	
informal credit		-0.029		0.201
formal credit		0.019		-0.021
credit	-0.025		0.140	
weather shock	0.453***	0.456***	0.687***	0.588***
remittance	-0.000	-0.000	-0.000	-0.000
household size	0.049	0.050	0.039	0.041
child share	0.591	0.581	0.598	0.534
age head	0.001	0.002	0.001	0.002
school head	-0.044**	-0.043**	-0.045**	-0.046**
ethnic minority	1.617***	1.634***	1.617***	1.677***
phone	-0.028	-0.028	-0.034	-0.033
tractor	-0.224**	-0.220**	-0.232**	-0.218**
livestock	-0.000**	-0.000**	-0.000**	-0.000***
motorbike	0.030	0.032	0.048	0.055
owned farm land	0.146	0.157	0.147	0.156
land fragmentation	0.290**	0.286**	0.292**	0.312**
migration	0.273*	0.281*	0.259*	0.275*
non-farm employment	0.145	0.148	0.164	0.181
2010	-0.435**	-0.434**	-0.433**	-0.432**
2013	0.250	0.260*	0.245	0.243
Hatinh	1.631***	1.643***	1.622***	1.665***
Hue	1.113***	1.163***	1.086***	1.144***
weather shock (time average)	0.162	0.155	0.175	0.182
credit (time average)	0.508*		0.503*	
informal credit (time average)		0.492		0.554
formal credit (time average)		0.625**		0.581**
remittance (time average)	0.000	0.000	0.000	0.000
household size (time average)	-0.038	-0.045	-0.029	-0.043
child share (time average)	-0.676	-0.626	-0.670	-0.572
phone (time average)	-0.075	-0.084	-0.060	-0.078
farm machinery (time average)	0.508	0.481	0.504	0.465
livestock (time average)	0.000	0.000	0.000	0.000
motorbike (time average)	-0.527**	-0.526**	-0.542**	-0.543**
owned farm land (time average)	-0.114	-0.124	-0.128	-0.138
farm land fragmentation (time average)	-0.632	-0.594	-0.653	-0.631
migration (time average)	-0.033	-0.067	-0.023	-0.047
non-farm employment (time average)	-0.126	-0.136	-0.144	-0.144
Constant	-3.723***	-3.851***	-3.801***	-3.875***
No. of observations	3000	3000	3000	3000
Prob. > Chi^2	0.000	0.000	0.000	0.000

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

Appendix A5. Factors affecting household access to credit sources

	Simultaneous probit model			
	Access to informal credit		Access to formal credit	
	Coefficient	Std.	Coefficient	Std.
weather shock	0.093*	(0.056)	0.006	(0.056)
remittance	-0.000	(0.000)	-0.000*	(0.000)
household size	0.069***	(0.024)	0.023	(0.018)
child share	0.004	(0.163)	-0.221	(0.136)
age head	-0.009***	(0.003)	-0.006**	(0.003)
school head	-0.028***	(0.008)	0.008	(0.009)
ethnic minority	-0.264***	(0.095)	-0.066	(0.100)
phone	-0.013	(0.026)	0.030	(0.023)
tractor	0.006	(0.053)	0.068	(0.050)
livestock	-0.000**	(0.000)	0.000	(0.000)
motorbike	-0.094***	(0.035)	0.025	(0.035)
owned farm land	-0.024	(0.045)	0.018	(0.034)
farm land fragmentation	0.083	(0.055)	-0.047	(0.052)
migration	0.100*	(0.059)	0.154***	(0.056)
non-farm employment	-0.093	(0.061)	0.178***	(0.054)
2010	-0.304***	(0.076)	0.096	(0.076)
2013	-0.390***	(0.067)	-0.025	(0.059)
Ha Tinh	-0.525***	(0.094)	-0.154	(0.111)
Hue	-0.737***	(0.092)	-0.330***	(0.094)
Constant	0.587***	(0.218)	-0.376*	(0.227)
No of observations	3000			
Wald $chi^2(38)$	326.80			
Prob. > chi^2	0.000			

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