Environmental Challenges 6 (2022) 100430

Contents lists available at ScienceDirect

Environmental Challenges

journal homepage: www.elsevier.com/locate/envc

Shock, risk attitude and rice farming: Evidence from panel data for Thailand

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ARTICLE INFO

Keywords:
Shock experience
Risk attitude
Input application
Rice production
Technical efficiency
Thailand

ABSTRACT

Rice is one of the most important crops for food security and rural livelihoods in many developing countries in Asia. However, the current rice farming practices heavily rely on synthetic fertilizers and pesticides that pose a significant threat to the environment. Further, the overuse of inputs might lead to the wastage of resources. Therefore, this research examines the impact of shocks experienced by farmers on their risk attitude, input use, and technical efficiency in rice farming. We use a balanced panel dataset of 1220 rice households from Thailand collected in 2013 and 2017 and employ a fixed-effects estimation with instrumental variables to account for endogeneity concerns. Our results show that fertilizers and pesticides are risk-decreasing inputs, which means rice farmers, who are more unwilling to take risks, tend to apply more fertilizers and pesticides. Adverse shocks affect rural households' risk attitudes, leading to over applications of fertilizers and pesticides and, therefore, reducing farming efficiency. We suggest that policies providing crop insurance and enhancing farmers' awareness on proper input application are critical to mitigate the adverse impacts of shocks and reduce the inefficient use of these chemical inputs.

1. Introduction

Rice is one of the most important crops for food security and rural livelihoods in many developing countries, especially in the Southeast Asia region (Kajisa and Akiyama, 2005). Rice farming plays a crucial role in income generation and ensuring food security for millions of rice farmers in Southeast Asian countries (Suebpongsang et al., 2020; Giesecke et al., 2013) and contributes to food security at the global level through rice export. However, the current rice farming practices heavily rely on synthetic fertilizers and pesticides (Berg and Tam, 2012; Grovermann et al., 2013; Panuwet et al., 2012) for higher productivity through improving soil health and preventing damages caused by crop pests and diseases (Möhring et al., 2020; Shankar et al., 2008). Synthetic fertilizers and pesticides are the inputs that farmers cannot self-produce and have to rely on purchase, and the expenses on these inputs usually account for a high proportion of production costs. Therefore, overuse of these inputs lowers rice production efficiency and income from rice farming (Nguyen et al., 2017). Furthermore, overusing chemical inputs poses a major threat to agricultural sustainability (Byrareddy et al., 2019), negatively affecting both underground and surface water, and creating eutrophication and losses of biodiversity (Damalas and Eleftherohorinos, 2011; Liu et al., 2013; Yadav et al., 1997).

Empirical evidence for explaining the overuse or inappropriate application of synthetic fertilizers and pesticides points out several factors such as farmers' lack of knowledge about optimal levels of input use, significant influence of input suppliers, weak management from authorities, and risk aversion under uncertainties caused by fake products, asymmetric market information of inputs, soil quality, pests and diseases, and climatic variability (Babcock, 1992; Isik and Khanna, 2003; Khor et al., 2018; Salazar and Rand, 2020). For instance, Feder (1979) reported that a lack of information about the degree of pest infestation and pesticide' effectiveness was driving risk-averse farmers to apply more pesticides to reduce the impact of risks. Supporting this finding, Khor et al. (2018) indicated that the fear of low-quality fertilizers (fertilizers' effectiveness) might be an uncertainty encouraging farmers to apply more fertilizers. Unpredictable climatic conditions could also influence the intensity of fertilizers (Babcock, 1992; Isik and Khanna, 2003). Under risk aversion, these uncertainties become significant determinants of fertilizer and pesticide use (Babcock, 1992; Pannell, 1991). Hence, examining the influence of risk attitude in uncertain contexts on the application of fertilizers and pesticides deserves attention.

Rural households in developing countries live in a vulnerable context (Nguyen and Nguyen, 2020; Poggi, 2019; Takasaki, 2018), fre-

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https://doi.org/10.1016/j.envc.2021.100430
Received 5 October 2021; Received in revised form 18 December 2021; Accepted 18 December 2021

quently facing different types of shocks such as weather shocks and crop pests/diseases (Klasen and Waibel, 2015; Nguyen et al., 2020). These shocks create uncertainties that influence farmers to use more/less inputs. For instance, frequent weather shocks such as floods, landslides, and storms might, on the one hand, discourage rural households from applying an adequate amount of inputs because of their fear of losses. On the other hand, droughts might indirectly and adversely affect systemic insecticides' performance that leads to an increase in pesticide use (Khodaverdi et al., 2016). Consequently, farmers might disregard recommended optimal input application rates in the context of uncertainties (Babcock, 1992). Unfortunately, a limited number of studies account for these shocks in examining the relationship between farmers' risk attitude and input application.

Adverse shocks might have a direct impact on the production of rural households by destroying output (or income) and physical assets. They might also have an indirect effect by altering farmers' behavior towards risks. Under dysfunctional and flawed insurance markets, rural households in developing countries have become more risk-averse (i.e., unwilling to take risks) after experiencing covariate and idiosyncratic shocks (Gloede et al., 2015; Liebenehm, 2018). However, just a few studies take shock experience and farmers' risk attitude in examining their impacts on crop production. While these previous studies provide important insight, there are a number of research gaps that need further investigation. First, the endogeneity of risk aversion has not been addressed. Second, while rural households in developing countries have to cope with a wide range of shocks and production risks, previous studies mainly considered droughts and crop pests in the analysis disregarding other shocks such as floods, storms, and diseases. Third, previous studies did not examine how changes in farmers' risk attitude impact farming efficiency to validate whether farmers' application of pesticides and fertilizers is efficient, especially for risk-averse farmers.

Against this background, we use a panel dataset collected in Thailand (a country in the Southeast Asia region) to (i) examine the impacts of risk attitudes on fertilizer and pesticide use, and (ii) investigate the effect of adverse shocks and risk attitudes on technical efficiency in rice production. Thailand is relevant because agricultural production plays an important role in its rural economy (Suebpongsang et al., 2020; Poggi, 2019). Addressing these research questions is necessary for policy responses to the harmful impacts of the inefficient application of synthetic fertilizers and agrochemicals on rural households' production and the environment.

The rest of the paper is as follows. Section 2 reviews the literature. Section 3 introduces the study sites and data. Section 4 describes the methods for data analysis. Section 5 discusses the findings. Section 6 concludes with policy recommendations.

2. Literature review

Although the relationship between risk attitude and input application has been examined in a few studies, the findings on the roles of pesticides and fertilizers show mixed directions (Möhring et al., 2020; Paulson and Babcock, 2010). Fertilizers are generally considered risk-increasing inputs. However, they could also play a risk-decreasing role (Babcock, 1992; Paulson and Babcock, 2010). For instance, Rajsic et al. (2009) found that nitrogen was a risk-increasing input, implying that risk-averse farmers tend to apply less nitrogen. This finding is supported by Möhring et al. (2020). On the contrary, Khor et al. (2018) stated that less wealthy farmers had a lower level of fertilizer use when their risk aversion increased. This finding aligns with Salazar and Rand (2020) that fertilizers are risk-decreasing inputs. Farmers who are more unwilling to take risks might overuse fertilizers because they think the crops need an additional amount of fertilizers (Babcock, 1992).

With regard to pesticides, a key motivation behind the application of pesticides is to provide a means of insurance against yield losses/damages caused by pests and diseases (Feder, 1979; Norgaard, 1976). These studies revealed that the higher the degree of uncertainty regarding pests' damages, the higher the volume of pesticide application, despite any given levels of pest infestation and pesticide costs. Liu and Huang (2013) confirmed the risk-reducing role of pesticides. Nevertheless, pesticides could also play a risk-increasing role (Horowitz and Lichtenberg, 1994). Möhring et al. (2020) pointed out that risk attitudes affect differently on pesticide use depending on the types of pesticides. Recently, Salazar and Rand (2020) examined the impacts of production risks on pesticide use and concluded that pesticides are risk-increasing inputs when more risk-averse rice producers apply fewer pesticides.

Although these previous studies provide important insight on the association between risk attitude and input application, there are a number of research gaps that need further investigation. First, farmers in developing countries live in a highly vulnerable environment with a wide range of adverse shocks (Isik and Khanna, 2003; Nguyen et al., 2020). However, only a few studies simultaneously take these aspects into account when estimating the impact of risk attitude on crop production. Rural households' behavior under risks might explain low agricultural productivity, vicious cycles of poverty, and determination of risk-aversion in the loss domain to maximize investment decisions (Sagemüller and Mußhoff, 2020). Uncertainties caused by adverse shocks affect rural households' risk attitudes that might lead to improper applications of inputs and, therefore, reduce technical efficiency (TE). In this case, their fear of uncertainties may encourage them to apply more inputs than efficient levels, and this overuse is wasteful and harmful for the environment and their health. As a result, farmers with high levels of risk aversion could culminate in economic decisions that lead to relatively less income (Gloede et al., 2015). Thus, accounting for diverse shock types in estimating input application still deserves further attention. Second, farmer's risk attitude is endogenous. There is a significant and robust linkage between risk aversion and wealth levels in the form of income or assets of the households (Sagemüller and Mußhoff, 2020). Farmers' risk attitude can also be affected by household characteristics such as age, education, and gender (Gloede et al., 2015). Externalities can further influence the risk aversion of rural households in the form of adverse shocks (Liebenehm, 2018; Sagemüller and Mußhoff, 2020). Therefore, estimations of input use and risk preferences ignoring these aspects might produce biased results due to the problem of endogeneity. Third, farmers' risk aversion might change overtime; however, most previous studies on risk attitude and input application in developing countries relied on cross-sectional data (Khor et al., 2018; Salazar and Rand, 2020; Liu and Huang, 2013) because long-term panel data with information on risk aversion might not be available. Thus, using panel data for this type of study is relevant to produce more reliable evidence since it allows to control for unobserved sources of heterogeneity (Millimet and McDonough, 2017; Nguyen et al., 2021; Ward, 2016).

Hence, our study contributes to filling these research gaps. We simultaneously examine the impact of risk attitudes and shocks on input application and technical efficiency in rice production. By employing a balanced panel dataset of rice producers in Thailand, we first investigate the association between risk attitude and input use in the context of shocks. We control for the potential endogeneity of risk attitude by employing an instrumental variable (IV) regression. Then, we estimate the technical efficiency in rice production through a stochastic frontier model for panel data proposed by Greene (2005) to justify the effects of improper input application caused by farmers' risk attitudes and shocks. One of the advantages of this model is that it allows us to estimate time-variant efficiency and can distinguish the unobserved heterogeneity from the inefficiency component (Nguyen et al., 2021). The findings are expected to enrich the literature on risk attitude and chemical input application and provide useful insight for formulating public policies to mitigate the negative impacts of shocks, improve production efficiency, and reduce the harmful effects of chemical overuse on the environment.

3. Study sites and data

3.1. Study sites and data sources

Data for this research are from the *"Poverty dynamics and sustainable development: A long-term panel project in Thailand and Vietnam (*www.tvsep.de*)"*, funded by the German Research Foundation (Deutsche Forschungsgemeinschaft - DFG-FOR 756/2). This project aims to generate a better and in-depth understanding of income and vulnerability to poverty dynamics in rural regions of the emerging economies of Thailand and Vietnam. Following the guidelines of the Department of Economic and Social Affairs of the United Nations (United Nations, 2005), the sampling process included a three-stage stratified random sampling procedure based on the administrative system of each country. In Thailand, the survey was conducted in three provinces, namely Buriram, Nakhon Phanom, and Ubon Ratchathani (see Fig. 1 for the study sites), where majority of the households live in rural area and are dependant on agriculture for their livelihood. In the first stage, sub-districts were selected in each province. Then, two villages were chosen with a probability proportional to the size of the population. At the third stage, a random selection of ten households was made based on the list of all households in the sampled villages with equal probability (see Nguyen et al. (2017), Klasen and Waibel (2015) for detailed information of the survey's designation and implementation). For this research, we use a balanced panel of 1220 rice farmers collected in 2013 and 2017.

In this survey, the information of risk attitude is a self-assessment scale similar to the one in the German Socioeconomic Panel conducted by the German Institute for Economic Research. In this self-assessment, the respondents (normally the household's head) were asked to self-evaluate their risk attitude on a shown scale ranging from zero (= unwilling to take risks) to ten (= fully prepared to take risks). Although this kind of self-assessment might not perfectly reflect risk attitude, it has been validated as an appropriate indicator for respondents' risk preferences (Liebenehm, 2018; Hardeweg et al., 2013) and has been widely applied in studies on risk preferences (Khor et al., 2018).

With regard to shock experience, the respondents were asked to report shock events that they experienced in the reference period *"Was your household affected by any of the following [events] between 1st May 20XX to 30th April 20XX"*. The length of the reference period was defined by the gap between the current and previous waves. In this research, we focus on weather shocks (including floods, droughts, landslides, erosion, and storms), crop pests and diseases (Nguyen and Nguyen, 2020). We take the respondents' exposure to shocks in the last 12 months into account as indicators of shock impacts such as production costs, yield, and efficiency are based on a 12-month recall period. We prevent misreported shocks of respondents by cross-checking between reported shocks and their losses (income, extra expenditure, or assets) due to the events. Then, we generate a dummy variable of households who are exposed to weather shocks, crop pests and diseases. These reported shocks are strongly relevant to agricultural production in rural areas in developing countries (Nguyen et al., 2020).

In the TVSEP data, input costs are recorded with a wide range of cost categories such as land preparation, seedling, weeding, fertilizers, pesticides, irrigation, harvest costs, and other costs. The other costs include additional costs that do not fit any in the listed cost categories, for example, of pre-processing before selling. This study uses fertilizer volume, fertilizer expenditure, and pesticide expenditure as key variables to analyse the impacts of farmers' risk attitudes on input applications. We use the expenditure on pesticides instead of quantity use because the data do not record the amount of pesticides. We control for price differences by using constant monetary values adjusted to 2005 prices.

3.2. Data description

Besides key variables, namely farmers' risk attitudes, rice production, and shocks, we control for other characteristics of rice farm households such as household's demographic characteristics, farming characteristics, physical capital, and village characteristics (see Appendix 1 for the names, measurement, and definitions of variables). Table 1 provides a descriptive summary of the data. The descriptive statistics show significant differences in rice output, expenditures on fertilizers, pesticides, seedling, weeding, irrigation, and other costs, but not the fertilizer quantity, land preparation costs, and harvest costs between 2013 and 2017. While the use of inputs is higher, the rice productivity was lower in 2013 than in 2017. The average farming area of rice farmers in Thailand is about 3.24 hectares (ha), and approximately two household labourers engage in farming activities. The experience of shocks appears to be different over time. Particularly, farmers reported more weather shocks in 2013 but almost the same level of crop pests in 2013 and 2017.

Overall, farmers who experience shocks appear to significantly have lower rice yield, lower expenditure on land preparation, higher expenditure on fertilizers, pesticides, seedling, and other costs, while fertilizer use (in quantity) and expenditures on weeding, irrigation, and harvest are not significantly different. Households experiencing shocks have larger farming areas and more household members engaging in agriculture than non-shock households. Households with shock experience also tend to have a lower level of willingness-to-take risks than the households without shock experience.

Table 2 shows the demographic characteristics, farming characteristics, physical capital, and village characteristics of rice farmers in Thailand. The average age of the households' head is about 60 years old with around five years of schooling. The household size and dependency ratio are significantly different both between 2013 and 2017 and between shock and non-shock groups. On average, rice farm households in Thailand have about five members. The average distance from farmers' house to all land plots is 2.23 km. The village characteristics show that the vast majority of households in rural Thailand have access to electricity (more than 97%), but only a small percentage of them have cable internet at home (about 3%).

4. Methods

4.1. Examining the impacts of shocks and risk attitudes on fertilizer and pesticide use

We start with the estimation of input application specified as follows:

$$Y_{ijt} = \varphi R_{it} + \phi S_{it} + \psi H_{it} + \theta V_{jt} + \varepsilon_{ijt} \tag{1}$$

In Eq. (1), Y_{ijt} denote the dependant variables: fertilizer use (kilograms per ha in natural logarithm), fertilizer expenditure, and pesticide expenditure (both in PPP$ per ha in natural logarithm). R_{it} representing the risk attitude of household i from village j at time t. This variable is treated as an endogenous variable and, therefore, is estimated with instrumental variables. S_{it} reflects shock variables which are weather shocks, crop pests and diseaseas. H_{it} is a group of household and farm characteristics, namely demographic characteristics, farm characteristics, and physical capital. V_{jt} consists of village characteristics of village j at time t, ε_{ijt} is the error term.

Regarding the instrumental variables, previous studies pointed out that wealth levels and ages of households' heads strongly correlate with the risk attitudes (Gloede et al., 2015). Therefore, we use two external variables at sub-district levels, namely, the average area of farmland to represent the wealth, and the average age of households' heads as the

Fig. 1. Study sites in Thailand under the TVSEP project.

Table 1
Descriptive summary of risk attitudes, rice production, and shock experience of rice farmers in Thailand.

	Whole sample	By year		By shock group	
	(n = 2440)	2013(n = 1220)	2017(n = 1220)	Non-shock(n = 1514)	Shock(n = 926)
Risk attitude	5.59	4.80	6.38***, a	5.74	5.35***, a
	(3.07)	(2.68)	(3.24)	(3.10)	(3.01
Rice production					
Rice yield	2111.21	1960.67	2261.74***, a	2227.86	1920.48***, a
(kg/hectare)	(987.57)	(1057.43)	(887.63)	(945.37)	(1025.24)
Fertilizer volume (kg/hectare)	83.66	87.9	79.42 a	84.39	82.48 a
	(152.10)	(170.67)	(130.86)	(156.42)	(144.84)
Fertilizer cost (PPP$/hectare)	214.25	271.68	156.83***, a	199.59	238.22***, a
	(291.64)	(392.97)	(95.68)	(286.04)	(299.19)
Pesticide cost (PPP$/hectare)	11.41	13.65	9.16***, a	9.45	14.60***, a
	(27.26)	(33.18)	(19.38)	(23.43)	(32.33)
Land preparation cost	107.29	104.5	110.08 a	110.81	101.53**, a
(PPP$/hectare)	(86.82)	(107.62)	(59.03)	(96.16)	(68.53)
Seedling cost (PPP$/hectare)	34.83	55.54	14.11***, a	31.39	40.45**, a
	(90.81)	(118.36)	(40.37)	(88.01)	(94.98)
Weeding cost (PPP$/hectare)	22.54	44.07	1.01***, a	22.83	22.07 a
	(109.28)	(151.37)	(7.49)	(115.62)	(98.11)
Irrigation cost (PPP$/hectare)	2.1	3.18	1.02**, a	1.93	2.37 a
	(20.76)	(27.98)	(8.78)	(22.66)	(17.22)
Harvest cost	153.84	151.07	156.62 a	151.68	157.38 a
(PPP$/hectare)	(125.8)	(158.48)	(80.83)	(122.26)	(131.37)
Other costs	6.1	0.16	12.03***, a	7.6	3.64***, a
(PPP$/hectare)	(15.75)	(2.48)	(20.49)	(17.48)	(12.03)
Farming area	3.24	4.35	2.13***, a	2.93	3.75***, a
(hectares)	(3.59)	(4.37)	(2.05)	(3.01)	(4.32)
Farming labour	2.36	2.49	2.23***, a	2.33	2.40 a
(labourers)	(1.11)	(1.20)	(0.99)	(1.13)	(1.08)
Shocks					
Weather shock†	0.34	0.48	0.20***, b		
	(0.47)	(0.50)	(0.40)		
Pest and diseas†	0.09	0.08	0.09 b		
	(0.28)	(0.28)	(0.29)		

Standard deviations in parentheses; Statistic tests between years and households without- with shock experiences;.
* p<0.1.
[a] Two-sample t-test.
[b] Non-parametric two-sample rank-sum test; †: Dummy variable.
*** $p < 0.01$.
** $p < 0.05$.

IVs (see Appendix 2 for the validation of these IVs). The intuition behind this selection is that wealthier families tend to have a better cushion against adverse outcomes caused by uncertainty. Younger people appear to be more willing to take risks than older people (Gloede et al., 2015). Further, we conduct several quality tests, namely underidentification test, weak identification test, and Sargan-Hansen statistic test for over-identifying restrictions to confirm the appropriateness of these IVs. The results of these tests presented on the last three rows of Table 3 demonstrate the appropriateness of these IVs. We further check for multi-collinearity problems amongst independent variables. The results of the variance inflation factor (VIF) values indicate no signs of this problem (see Appendix 3 for the VIF values). With regard to the estimation method, we use a two-stage least squares fixed-effects panel estimation with IVs to analyse the impacts of shocks and risk attitudes on input applications. Finally, we implement all estimations with standard errors clustered at the village level to reduce the possible spatial autocorrelation.

4.2. *Investigating the effects of risk attitudes and adverse shocks on technical efficiency in rice production*

As risk attitudes of farmers might lead to improper applications of fertilizers and pesticides, they would result in a greater inefficiency of farming. We first estimate rice production's technical efficiency to address this question. Although the Cobb-Douglas functional form was widely employed to estimate technical efficiency (Deininger et al., 2008; Chamberlin and Ricker-Gilbert, 2016), the translog functional form using the stochastic frontier model (SFM) has become more popular in the estimation of technical efficiency of farming because it is more flexible than the Cobb-Douglas functional form and farmers operate in uncertain environments, and are exposed to various production risks (Nguyen et al., 2021, 2018). Since the standard panel data model for conducting SFM might have constant inefficiency overtime and the homoscedasticity of the error and inefficiency terms (Nguyen et al., 2021), we apply the true random-effects model proposed by Greene (2005) that can differentiate between the unobserved heterogeneity and the inefficiency component. This true random-effects model is specified as:

$$Q_{it} = \alpha + \omega_i + f\left(X_{it};\beta\right) - u_{it} + v_{it} \tag{2}$$

In Eq. (2), Q_{it} is the farm's output (in logarithm form) of firm i in time t, $f(X_{it};\beta)$ represents the production technology of each farmer, including input vectors X_{it} and their associated vectors β, u_{it} represents the time-varying inefficiency term ($u_{it} \sim N^{+}(0,\delta^2_{it}) = N^{+}(0,\ \exp(\omega_{u0} + Z'_{u,it}\omega_u)$, v_{it} denotes the random two-sided noise term (($v_{it} \sim N^{+}(0,\delta^2_{v})$), and ω_i ($\omega_{it} \sim N^{+}(0,\delta^2_{\omega})$) is the specific random term that is time-invariant and can capture firm-specific heterogeneity. This heterogeneity term ω_i has an *iid (independent and identically distributed)* normal distribution in this true random-effects model (Abdulai and Tietje, 2007). We follow the translog specification from Poggi (2019) to estimate rice production function as:

$$ln\ Y_{it} = \alpha + \omega_i + \sum_m \beta_m lnX_{itm} + \frac{1}{2}\sum_m \sum_n \beta_{mn} lnX_{itm} lnX_{itn} - u_{it} + v_{it} \tag{3}$$

In Eq. (3), $ln\ Y_{it}$ is the rice yield (kilograms per ha) of household i at time t in natural logarithm; lnX_{it} are the vectors of key input use and relevant production-related data of the household i at time t in natural

Table 2
Descriptive summary of household characteristics, farming characteritics and physical capital of rice farmers in Thailand.

	Whole sample	By year		By shock group	
	(n = 2440)	2013(n = 1220)	2017(n = 1220)	Non-shock(n = 1514)	Shock(n = 926)
Demographic characteristics					
Male head†	0.72	0.74	0.70**, [b]	0.71	0.73 [b]
	(0.45)	(0.44)	(0.46)	(0.45)	(0.44)
Age of head (years)	59.7	58.45	60.96***, [a]	59.83	59.50 [a]
	(11.71)	(12.02)	(11.25)	(11.58)	(11.91)
Ethnicity of head†	0.95	0.93	0.96***, [b]	0.95	0.95 [b]
	(0.23)	(0.26)	(0.19)	(0.23)	(0.22)
Education of head (years)	4.92	4.83	5.00 [a]	4.98	4.82 [a]
	(2.67)	(2.69)	(2.65)	(2.72)	(2.58)
Household size (persons)	5.06	5.25	4.86***, [a]	5.00	5.15*, [a]
	(1.85)	(1.86)	(1.81)	(1.86)	(1.83)
Dependency ratio	1.40	1.54	1.27***, [a]	1.38	1.43*, [a]
	(0.74)	(0.74)	(0.71)	(0.73)	(0.75)
Farming characteristics					
Distance to land plots (km)	2.23	2.48	1.98 [a]	2.39	1.97 [a]
	(10.96)	(14.36)	(5.84)	(13.22)	(5.57)
No of tractors	0.69	0.71	0.68 [a]	0.68	0.70 [a]
	(0.62)	(0.62)	(0.62)	(0.62)	(0.62)
No of sprayers	0.57	0.46	0.68***, [a]	0.55	0.60 [a]
	(0.92)	(0.92)	(0.91)	(0.86)	(1.02)
No of water pumps	0.52	0.49	0.56***, [a]	0.53	0.52 [a]
	(0.71)	(0.69)	(0.73)	(0.72)	(0.69)
Physical capital					
No of motorcycles	1.57	1.54	1.59 [a]	1.57	1.56 [a]
	(0.91)	(0.93)	(0.90)	(0.89)	(0.95)
No of pushcarts	0.53	0.47	0.60***, [a]	0.55	0.50**, [a]
	(0.58)	(0.55)	(0.60)	(0.55)	(0.62)
No of pickups	0.35	0.33	0.37*, [a]	0.36	0.33 [a]
	(0.56)	(0.55)	(0.57)	(0.57)	(0.56)
No of trucks	0.06	0.05	0.06 [a]	0.05	0.06 [a]
	(0.27)	(0.27)	(0.26)	(0.25)	(0.30)
Asset value per capita (PPP$)	2119	1881.23	2356.77***, [a]	2128.31	2103.77 [a]
	(3905.64)	(3649.15)	(4134.14)	(3453.45)	(4551.18)
Village characteristics					
Access to electricity	0.98	0.97	0.99***, [a]	0.98	0.97**, [a]
	(0.12)	(0.16)	(0.04)	(0.10)	(0.14)
Home cable internet	0.03	0.03	0.04**, [a]	0.03	0.03 [a]
	(0.08)	(0.09)	(0.06)	(0.07)	(0.09)

Standard deviations in parentheses; Statistic tests between years and households without- with shock experiences;.
[a] Two-sample t-test.
[b] Non-parametric two-sample rank-sum test; †: Dummy variable.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

logarithm. In this study, we include farming area, cost of land preparation, cost of seedling, cost of weeding, cost of fertilizers, cost of pesticides, cost of irrigation, cost of harvest, other costs, and farming labour. The other costs include additional costs that do not fit in any of the listed categories of costs, and this category captures the cost, for example, of pre-processing before selling. These costs are measured in PPP$ (adjusted to 2005 prices); ω_i is the time-invariant and farm-specific heterogeneity.

We include the correlated random-effects (CRE) values suggested by Mundlak (1978) to address the engogeneity problem of relevant variable omission and reverse causality due to the joint determination of input and output (Nguyen et al., 2021; Gautam and Ahmed, 2019; Lien et al., 2018). Further, in Eq. (3), all input variables are normalised as $\ln(X^*_{itm}) = \ln(\frac{X_{itm}}{\bar{x}_m})$ by their respective mean before the estimation to allow us to interpret the estimated coefficients as elasticities at means (Nguyen et al., 2021; Holtkamp and Brümmer, 2017). We run the true random-effects SFM with the maximum likelihood method (Belotti et al., 2013) and predict the farm technical efficiency (TE) of household i at time t as:

$$TE_{it} = \mathrm{E}\left[\exp\left(-u_{it}\right)\left|\left(v_{it} - u_{it}\right)\right.\right] \tag{4}$$

In the final step, we take the farming efficiency scores (TE_{it} in Eq. (4)) as the dependant variable to analyse the influence of farmers' risk attitudes and shocks on farming technical efficiency. The panel model of the farming efficiency of household i from village j at time t (TE_{ijt}) is expressed as follows:

$$TE_{it} = R_{it}\varphi' + S_{it}\phi' + H_{it}\Psi' + V_{jt}\theta' + \zeta_{ijt} \tag{5}$$

In Eq. (5), the independent variables remain the same as what we use in Eq. (1), namely farmers' risk attitudes, shocks, household and farm characteristics, and village characteristics. The risk attitude variable is also instrumented in the estimation of farming efficiency. Besides the fixed-effects estimation with risk attitude scores, we run three additional IV fixed-effects estimations with dummy variables of farmers' risk attitude. We classify farmers into three groups, namely risk-averse (those have risk attitude scores lower than five), risk-neutral (those have the scores of five), and risk-taking (those have the scores higher than five) to examine the correlation between shocks, risk attitude, and farming efficiency in different risk attitude levels. We conduct three quality tests (underidentification test, weak identification test, and Sargan-Hansen test for over-identifying restrictions) to confirm the appropriateness of the IVs for these estimations. The results of these tests validate the appropriateness of these IVs (except for the case of risk-neutral estimation) (results of these tests are presented in Table 5). Finally, standard errors are also clustered at the village level.

Table 3
Impacts of shocks and risk attitudes on fertilizer and pescide use (IV fixed-effects).

	Pesticide expenditure (ln)	Fertilizer volume (ln)	Fertilizer expenditure (ln)
Risk attitude	-0.116*	-0.093*	-0.234***
	(0.066)	(0.049)	(0.052)
Weather shock†	0.324***	0.011	0.066
	(0.089)	(0.067)	(0.079)
Pest and disease†	0.302**	0.304***	-0.007
	(0.146)	(0.091)	(0.110)
Male head†	0.147	0.067	-0.014
	(0.167)	(0.115)	(0.157)
Age of head	-0.007	0.008	0.002
	(0.007)	(0.005)	(0.005)
Ethnicity of head †	0.581***	0.540**	0.138
	(0.216)	(0.226)	(0.293)
Education of head	-0.027	0.027	0.034
	(0.029)	(0.020)	(0.023)
Household size	0.002	0.029	-0.004
	(0.032)	(0.023)	(0.027)
Dependency ratio	-0.107	-0.105**	-0.070
	(0.069)	(0.047)	(0.056)
Farming area	-0.004	-0.020**	-0.011
	(0.015)	(0.010)	(0.011)
Distance to land plots	0.000	0.004**	0.003*
	(0.002)	(0.002)	(0.002)
No of tractors	0.140	-0.033	0.022
	(0.106)	(0.073)	(0.092)
No of sprayers	0.189***	0.062*	0.085**
	(0.063)	(0.035)	(0.039)
No of water pumps	-0.055	0.027	-0.016
	(0.066)	(0.049)	(0.053)
No of motorcycles	0.060	0.069*	0.013
	(0.050)	(0.041)	(0.044)
No of pushcarts	0.100	0.079	0.018
	(0.072)	(0.061)	(0.071)
No of pickups	0.030	-0.054	-0.075
	(0.105)	(0.079)	(0.080)
No of trucks	0.274	0.070	-0.182
	(0.201)	(0.145)	(0.143)
Asset poor†	-0.190	-0.118	0.044
	(0.124)	(0.081)	(0.099)
Access to electricity (village variable)	0.286	0.327	0.363
	(0.203)	(0.334)	(0.388)
Home cable internet	0.262	-0.244	0.130
(village variable)	(0.421)	(0.270)	(0.326)
Constant	1.000*	2.824***	5.601***
	(0.544)	(0.496)	(0.584)
Number of observations	2440	2440	2440
Wald chi2(19)	119.250	252.340	424.330
Prob > chi2	0.000	0.000	0.000
Under identification	0.000	0.000	0.000
Over identification	0.375	0.761	0.432
Weak identification	26.862	26.862	26.862

Robust standard errors clustered at village level in parentheses; †: Dummy variable.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$. The under-identification test is an LM test based on the rk LM statistics (Kleibergen and Paap, 2006). The null hypothesis of this LM test indicates that the model is under-identified. The over-identification test relied on the Hansen J test with the null hypothesis indicating that all of the instruments are valid in the model. The reported values of under-identifying and over-identifying tests are p-values. The reported values of weak-identifying test are the Kleibergen-Paap rk Wald F statistics.

5. Results and discussion

5.1. Impacts of shocks and risk attitudes on input use in rice production

Table 3 shows the results of shocks and risk attitudes on fertilizer and pesticide use from the IV fixed-effects estimations. The instrumented risk attitude variable shows a negative impact on input applications with a significance at less than 10% level. This implies that both fertilizers and pesticides can be considered risk-reducing inputs in rice production in Thailand. The estimations of fertilizer use in both quantity and monetary values show almost the same effect of farmers' risk attitudes on the application of fertilizers. In other words, the more the farmers avoid risks, the more they apply fertilizers and pesticides. This also points out that becoming more risk-averse influences them to apply more inputs, even though these applications are improper. Our results remain consistent with lagged values of risk attitudes from the previous waves (see Appendix 4). Compared with a similar rice exporting country, our results of the correlations between risk attitude and input use support the findings

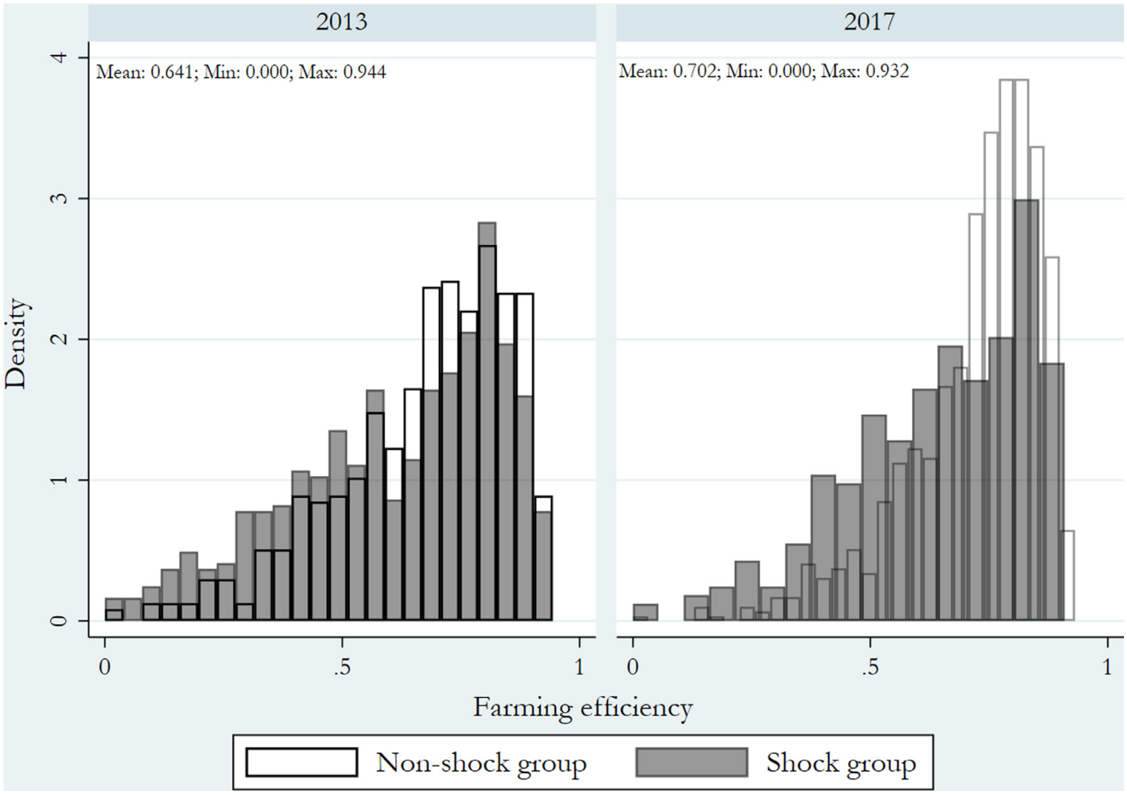

Fig. 2. Technical efficiency of rice farmers in Thailand between shock-experience groups.

from Salazar and Rand (2020) that fertilizers are risk-decreasing inputs in Vietnam, but pesticides have an opposite role. This difference can be because of the intensive level in rice production between the two countries or the biased results from the endogeneity problem unaddressed in their estimation. In short, uncertainties motivate rice farmers to use more fertilizers to enhance crops production because of their aversion behavior to losses (Sagemüller and Mußhoff, 2020).

Besides, Salazar and Rand (2020) found that droughts negatively affect pesticides use. This is contrary to our findings. The results from our IV estimations indicate that both shock types significantly and positively impact pesticide use. Notably, farmers who experience shocks are more likely to use up to 30% more pesticides than non-shock households. Furthermore, pests and diseases also have a significant and positive impact on fertilizer use with the same magnitude. In other words, these types of shocks are forcing farmers to use more these inputs. Therefore, stronger support from public services such as more efficient weather forecasts and local extensions in crop production are important to reduce the uncertainties in rural regions. In addition, providing a mechanism of crop production insurance to prevent adverse impacts of shocks might discourage farmers from overusing chemical inputs.

The IV fixed-effects estimations also show that households belonging to the Thai majority appear to use more inputs than minorities. This finding is in line with a case study in Vietnam (Baulch et al., 2007) that differences in ethnic groups are more likely to affect the application of production inputs due to their different farming practices and levels of wealth. Further, the results show that farmers having more agricultural equipment and transportation vehicles such as sprayers, motorcycles, and trucks tend to use more pesticides, which may be due to affordability to purchase or the ability to transport the inputs. For fertilizers, farmers with a higher education level, a longer distance to their land plots, more motorcycles appear to use more fertilizers, while those with a higher dependency ratio and larger farmland tend to use less fertilizers. The variable of asset poor shows an insignificant effect on input use.

Table 4
Brief results of the translog stochastic frontier production estimation of rice production from the true random-effects with Mundlak's adjustments (CRE).

	Coefficient	Robust S.E. [a]
ln farming area (a)	-0.040	0.051
ln land preparation cost (b)	-0.025	0.031
ln seedling cost (c)	0.005	0.016
ln weeding cost (d)	0.038*	0.020
ln fertilizer cost (e)	0.124***	0.037
ln pesticide cost (f)	0.024*	0.014
ln irrigation cost (g)	-0.029	0.021
ln other costs (h)	0.061***	0.017
ln farming labour (i)	-0.054	0.052
ln harvest cost (j)	0.098***	0.021
Mean variables of CRE		
ln farming area (time average-CRE)	0.045**	0.019
ln land cost (time average-CRE)	0.002	0.007
ln seedling cost (time average-CRE)	0.012***	0.004
ln weeding cost (time average-CRE)	-0.013**	0.005
ln fertilizer cost (time average-CRE)	0.024**	0.010
ln pesticide cost (time average-CRE)	0.005	0.004
ln irrigation cost (time average-CRE)	0.002	0.007
ln other costs (time average-CRE)	-0.015***	0.005
ln farming labour (time average-CRE)	0.026*	0.014
ln harvest cost (time average-CRE)	0.003	0.005
Constant	7.643***	0.136
No of observations	2440	
Log simulated-likelihood	-1749.885	
Sigma_u; Sigma_v; Lambda	0.492***; 0.209***; 2.359***	
Wald Chi2(75)	663.900	
Prob.	0.000	

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.
[a] Robust standard errors clustered at village level; ln: natural logarithm.

Table 5
Effects of shocks and risk attitudes on technical efficiency (IV fixed-effects).

	TE score	Group of risk attitudes		
		Risk averse	Risk neutral	Risk-taking
Risk attitude	0.021**			
	(0.009)			
Risk averse†		-0.225**		
(Risk attitude score <5)		(0.094)		
Risk neutral†			-0.240	
(Risk attitude score = 5)			(0.182)	
Risk taking†				0.128**
(Risk attitude score > 5)				(0.057)
Weather shock†	-0.079***	-0.077***	-0.079***	-0.077***
	(0.013)	(0.014)	(0.016)	(0.013)
Pest and disease†	0.014	0.015	0.010	0.013
	(0.021)	(0.023)	(0.021)	(0.020)
Male head†	-0.005	-0.007	-0.023	-0.015
	(0.026)	(0.028)	(0.031)	(0.026)
Age of head	-0.001	-0.001	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Ethnicity of head †	-0.032	-0.039	-0.005	-0.025
	(0.037)	(0.039)	(0.041)	(0.037)
Education of head	0.000	-0.000	0.003	0.001
	(0.004)	(0.004)	(0.005)	(0.004)
Household size	-0.005	-0.006	-0.002	-0.004
	(0.004)	(0.005)	(0.005)	(0.004)
Dependency ratio	0.000	0.004	-0.009	-0.002
	(0.010)	(0.011)	(0.009)	(0.009)
Farming area	-0.002	-0.003	-0.002	-0.002
	(0.002)	(0.002)	(0.003)	(0.002)
Distance to land plots	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.000)
No of tractors	0.003	0.002	0.012	0.007
	(0.014)	(0.015)	(0.015)	(0.014)
No of sprayers	-0.001	0.000	-0.002	-0.002
	(0.006)	(0.007)	(0.007)	(0.006)
No of water pumps	-0.008	-0.012	-0.003	-0.007
	(0.008)	(0.009)	(0.010)	(0.009)
No of motorcycles	0.018**	0.022**	0.007	0.015*
	(0.009)	(0.010)	(0.011)	(0.009)
No of pushcarts	0.014	0.010	0.019	0.013
	(0.012)	(0.014)	(0.014)	(0.013)
No of pickups	0.002	0.002	0.008	0.005
	(0.014)	(0.016)	(0.017)	(0.014)
No of trucks	-0.011	-0.003	-0.007	-0.004
	(0.031)	(0.029)	(0.042)	(0.032)
Asset poor†	0.010	0.016	-0.002	0.007
	(0.016)	(0.018)	(0.021)	(0.016)
Access to electricity	-0.111**	-0.110**	-0.107*	-0.111**
(village variable)	(0.051)	(0.051)	(0.061)	(0.054)
Home cable internet	0.083	0.022	0.156*	0.085
(village variable)	(0.083)	(0.094)	(0.090)	(0.079)
Constant	0.756***	0.949***	0.891***	0.808***
	(0.099)	(0.131)	(0.136)	(0.098)
Number of observations	2440	2440	2440	2440
Wald chi2(19)	265.760	208.880	284.310	308.200
Prob > chi2	0.000	0.000	0.000	0.000
Under identification	0.000	0.000	0.050	0.000
Over identification	0.072	0.141	0.027	0.063
Weak identification	26.862	12.053	3.087	25.639

Note: Robust standard errors clustered at village level in parentheses; †: Dummy variable.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$. The under-identification test is an LM test based on the rk LM statistics (Kleibergen and Paap, 2006). The null hypothesis of this LM test indicates that the model is under-identified. The over-identification test relied on the Hansen J test with the null hypothesis indicating that all of the instruments are valid in the model. The reported values of under-identifying and over-identifying tests are p-values. The reported values of weak-identifying test are the Kleibergen-Paap rk Wald F statistics.

5.2. *Effects of risk attitudes and shocks on technical efficiency in rice production*

To acquire the farming efficiency, we estimate the translog true random-effects stochastic production frontier function with Mundlak's adjustments (the Likelihood ratio test between the Cobb-Douglas and translog functional form in Appendix 7 shows that the translog form is more appropriate). Table 4 stacks the brief results of the estimation (full results in Appendix 6). Most of the mean variables of CRE show a statistical significance implying the presence of time-invariant unobservable characteristic effects (Gautam and Ahmed, 2019). Only five variables of inputs show a significant effect. This indicates the less intensive level of rice production in Thailand, compared with some competing countries such as Vietnam (Nguyen et al., 2021). The results also indicate that fertilizer is the most important input.

Fig. 2 shows the distribution of predicted farming efficiency scores. The mean score was 0.64 in 2013 and 0.70 in 2017, the vast majority of the households (about 85%) have a farming efficiency score higher than 0.50, and less than 3% of the households have an efficiency score higher than 0.90. The mean efficiency score of our estimation is slightly higher than the score of rice farmers in Thailand (0.63 from Rahman et al. (2009)), lower than Vietnam (0.75 from Nguyen et al. (2021) and of 0.85 from Huy and Nguyen (2019)), and higher than the scores of rice farmers in Cambodia (0.60) (Mishra et al., 2018) and in Bangladesh (0.57) (Mishra et al., 2015). In our result, the mean score of shock households appears to be lower than that of households in the non-shock group in 2013 and 2017.

Table 5 presents the effects of farmers' risk attitudes and shocks on technical efficiency in rice production and shows that farmers' willingness to take risks has a positive and significant effect on farming efficiency. This finding further suggests that higher risk-averse farmers are applying more fertilizers and pesticides, and this inefficient use of inputs causes farming inefficiency in their production. In addition, the result from IV fixed-effects estimations by groups of farmers' risk attitudes shows that households belonging to the risk-averse group appear to have lower farming efficiency. This confirms that more risk-averse farmers are inefficiently using chemical inputs, and this improper application leads to lower farming efficiency. Our findings support the conclusion that rural households' behavior under risk might explain low agricultural productivity and vicious cycles of poverty in developing countries (Sagemüller and Mußhoff, 2020) because these inputs account for a high proportion of production costs. We run additional estimations with lagged values of attitudes as robustness checks. The results remain consistent (see Appendix 5).

Unsurprisingly, weather shocks significantly and negatively affect rice technical efficiency, while pests and diseases show an insignificant influence in all IV fixed-effects estimations. Regarding the weather shocks, the result is related to the findings of Mishra et al. (2018) and Mishra et al. (2015) that weather shocks are a major reason affecting agricultural inefficiency in Cambodia and Bangladesh, respectively. This emphasizes the impacts of weather shocks on agricultural production in developing countries and urges governments to support rural households to cope with weather shocks, especially in the context of climate change that causes more frequent extreme weather events.

6. Conclusion

This study used balanced panel data of 1220 rice households in Thailand to examine the impacts of risk attitude on fertilizer and pesticide use and technical efficiency in the context of weather shocks, crop pests and diseases. Our study treated farmers' risk attitude as an endogenous variable to clarify empirical evidence of the correlations of risk aversion levels and input use. The IV fixed-effects estimations showed that fertilizers and pesticides are risk-reducing inputs in rice production in Thailand.

Our findings further showed that, in the context of weather shocks, crop pests and diseases, Thai farmers also tend to use more fertilizers and pesticides. Weather shocks significantly cause a significant decrease in their farm technical efficiency. This emphasizes the impacts of weather shocks on agricultural productions in developing countries and urges the governments to support rural households to cope with these shocks, especially in the context of climate change. We also found that rural households' behavior under risks could explain low agricultural productivity due to their risk aversion in the loss domain. Uncertainties caused by adverse shocks affect rural households' risk attitude, leading to improper application of inputs and, therefore, reducing farming efficiency. Hence, the governments in developing countries having similar characteristics as Thailand (e.g., Vietnam, where rice production also plays an important role and its rural population is vulnerable to shocks) should stimulate policies on providing crop production insurance to prevent and mitigate adverse impacts of shocks and enhance farmers' awareness of input's inefficient use. Extension services and awareness on weather and pest/disease shocks, adaptation options, and proper input application should also be provided or improved.

Our study has some limitations. First, we did not evaluate pesticide use in terms of intensity and environmental efficiencies. Second, we also did not consider potential marginal costs, the impacts of agrochemical use on the local environment, and farmers' health due to the limitation of the data about environmental impacts. Future research can emphasize these aspects, such as the influence of pesticide applications on local farmers' health, more in-depth analyses of output prices and production, and environmental efficiencies of agricultural production in developing countries.

Declaration of Competing Interest

The authors declare that they have no conflict of interest in this research.

Acknowledgments

The authors would like to thank the respondents from the surveyed provinces for their kind support and cooperation. We acknowledge the financial support of the German Research Foundation (DFG - FOR 756/2) for the TVSEP project and appreciate the efforts of our colleagues at the Leibniz University Hannover for data collection and cleaning. MH Do would like to thank the German Academic Exchange Service (DAAD) for financial assistance. This paper was presented in a virtual conference titled *"Environmental Challenges and Agricultural Sustainability in Asia: Interlinkages and Future Implications,"* organized by the Asian Development Bank Institute on 8–10 December 2021. The views, information, or opinions expressed in the paper are those of the authors, and the usual disclaimer applies.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.envc.2021.100430.

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