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Ex-post study on Expected Utility of Weather Information: Quasi Experiment on Sri Lankan Paddy Farming

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ABSTRACT

Weather information creates certainty and confidence in farmers' minds, which reflect as expected utility. The expected utility helps them to use other inputs to obtain crop yields as the final value. Sri Lankan paddy farmers use both traditional and scientific weather information to capture the uncertainty of rainfall which mainly affects the cultivation decisions. No studies have been conducted in Sri Lanka to find out the impact of the expected utility, derived due to weather information by paddy farmers. To fill this gap, an ex-post valuation study was carried out as a quasi-experiment. A sample of 900 paddy farmers was selected as the control group (450) and the treated group (450) by multi-stage random sampling from six districts representing major cultivation patterns in Sri Lanka. The treated group was provided location-specific weather information as rainfall forecasts. The control group was assumed to be using traditional knowledge or general weather information. The baseline survey was conducted in 2016, while the end survey was conducted in 2018 using the same pre-tested structured questionnaire. The CRRA utility function was estimated to find the expected utility. Difference in Difference (DID) regression was used to quantify the effect of the treatment as the provision of location-specific rainfall forecasts by considering the differences in paddy yield per hectare per farmer as the dependent variable. The results revealed that the treated group derived the highest expected utility. The DID regression results revealed that the interaction was significant ($p<0.05$), and the coefficient of interaction was 960.54. Therefore, low-risk aversion can be achieved by provisioning location-specific weather information. Such effort is important to increase the full utilization of factors of Sri Lankan paddy production.

INTRODUCTION

Weather is a foremost risk factor that creates impacts on agriculture (Luseno *et al.,* 2003; Hussain, 2008). The combination of weather information and the other agricultural inputs produces crops. These crops generate monetary values (Bert *et al*., 2006; Kang *et al*., 2009; Lemos *et al*., 2014; Tall *et al*., 2018). Most farmers are risk-averse to common agricultural risks, including climate and weather risks (Dillon and Scandizzo, 1978; Binswanger, 1981; Sulewski and Kłoczko-Gajewska, 2014). Risk aversion due to a lack of precise information about risk preferences, negatively affects agricultural production (Pope, 1982; Chaos, 1996). When farmers need to perform a choice under uncertainty, more information is preferred over less (Morris and Shin, 2002). Therefore, studies have been carried out to find the value of weather information on risk reduction in agriculture (Mjelde *et al.,* 1988; Msangi *et al*., 2006).

Farmers use traditional knowledge to forecast weather generally (Orlove *et al*., 2010; Kalanda-Joshua *et al*., 2011). The development of meteorological science has created advanced scientific weather forecasting methods (Meinke and Stone, 2005). The weather information generated by these two systems is used simultaneously by farmers (Howden *et al*., 2007; Murphy, 2011; Auma, 2016). However, studies have predicted poor accuracy in traditional weather forecasts in the future due to climate change impacts (Adams *et al*., 1995; Anderson *et al*., 2015).

Consideration of information as an economic good has been criticized due to its different form and use from other goods (DeLone and McLean, 1992; Seddon *et al*., 1998). However, goods can be material or non-material in nature (Marshell, pp 62-63). Therefore, weather information also can be directly valued as an economic good. But the valuation is not easy and quite different from the valuation of physical goods (Jones *et al*., 2000; Msangi *et al*., 2006; Tall *et al*., 2018). The valuation of weather information has been difficult since, it has a dual role as an input in the production process or as provisioning of awareness (Bates, 1990). There are two modes of weather information valuation exist as ex-ante and ex-post studies. In ex-post analysis, the real net benefits are used to measure the actions related to the weather information. In contrast, simulated results are used in ex-ante studies (Msangi *et al*., 2006). The output with the presence of weather information is compared against the null situation under ex-post analysis (Mjelde *et al*.1988, Luseno *et al*. 2003, Lybbert *et al.* 2003).

Sri Lankan paddy farmers generally use traditional knowledge to forecast weather (Esham and Garforth, 2013). In contrast, the Department of Meteorology (DOM) provides scientific weather information (Bandara, 2010; Gunawardhana, 2015). Sri Lanka expects negative impacts of climate change on agriculture in the future (De Silva, 2007). The existing weather and climate information gap have been identified as a bottleneck that prevents climate change adaptation (NAPCC 2016-2025). Therefore, the DOM provides short-term & more farmer-centric weather information. Many studies have sufficiently revealed the existing traditional weather forecast methods and factors that affect climate change adaptation in Sri Lanka (Droogers, 2004; Senaratne and Scarborough,2011; Esham, and Garforth, 2013; Dharmarathna, 2014; Truelove *et al*., 2015). However, the valuation of weather information as an input related to crop production has not been carried out yet in Sri Lanka. The studies on existing weather information are important for developing more suitable weather information products to increase the climate change adaptation of farmers (Letson *et al*., 2001; Broad *et al*., 2002; Vogel *et al*., 2006). Therefore, the objective of the study was, to value Sri Lankan paddy farmers' expected utility of weather information as an ex-post study. Because, the expected utility that is based on weather information allows them to decide other agricultural input uses, i.e. amounts to be used and time of use in paddy cultivation.

METHODOLOGY

Expected utility of climate information

The Expected Utility Theory (EUT) describes; that people are approximately risk neutral when risks are small. The risk aversion rises exclusively because the utility function over wealth is concave in nature. It is meant that the person who possesses a differentiable utility function would take a sufficiently small risk for any positive expected value. Therefore, a risk-averse person prefers lower returns with known risks rather than higher returns with unknown risks. The EUT uses to explain the risk aversion for economically important significant risks rather than the small risks most of the time (Arrow, 1971; Rabin, 2013).

The valuation of weather information has been carried out by assessing the user's value of the information according to the user's objective(s) (Gleeson, 1960; Hallanger, 1963; Pope and Just, 1991; Chavas and Holt, 1996; Holt and Laury, 2002; Letson *et al*., 2009). Maximization of Expected Utility (EU) has been widely used as the objective function (Mjelde *et al*., 1989, Jones *et al.,* 2000). Constant Relative Risk Aversion (CRRA) has been considered a concave utility function of risk aversion to derive the EU in both ex-ante and ex-post studies (Parrt, 1964; Parrt, 1978; Mjelde *et al*., 1989; Messina *et al*., 1999; Jones *et al*., 2000; Pandey, 2007). In ex-post studies, the EU of the wealth of climate or weather information has been estimated with real production data and net profits (Pope and Just, 1991; Chavas and Holt,1996; Holt and Laury, 2002; Letson *et al*., 2009; Roudier, *et al*., 2012).

Eq (01)

$$U(w) = \frac{w^{(1-\varphi)}}{1-\varphi} \text{ Where, } w > 0, \varphi \neq 1$$

In the above CRRA utility function (Eq (01)), aversion to risk is captured in the degree of curvature of a nonlinear utility function. Here, utility (*U)* depends on farmer wealth (*w)* and constant relative risk aversion factor (φ) or in other words - arrow Pratt Risk aversion coefficient. Constant relative risk aversion factor (the absolute risk aversion) decreases with increasing initial wealth. For each forecast, farmers' decisions result utility values. So, the function U(y +W) –U (W) is used to have a null utility when the farmers' income is zero. According to the model as in Eq (2), it is assumed that farmers allocate land among different crops to maximize the expected utility of wealth (U) at the end of year *1* for expected weather conditions.

Eq (2)

$$EU = \frac{1}{(1-\varphi)} \times \left(\frac{1}{n} \sum_{i=1}^{n} \left(\left(\left(\sum_{i=1}^{m} y_{ij} \right) + w \right) \right)^{(1-\varphi)} - w_0^{(1-\varphi)} \right)$$

Where EU is expected utility for climate year i, W_0 is initial wealth,Y_{ij} is net returns for crop j and year i, n denotes the number of years, m is the number of crop enterprises. W is the farmers' wealth other than the current production. Net returns, Y_{ij}, from the *j*th crop enterprise is calculated from constant production costs and prices, and yields using the *i*th weather year. In this regard, $Y = (P.Q) - C$ is used to calculate Y. Here, P is the paddy selling price, Q is the quantity produced (in kg), and C is the Cultivation cost. A universally accepted scale is not available to measure risk aversion. The available risk aversion measurement scales have been created by considering the easiness, accuracy, recent developments of risk theory, and according to the studied sample (Abdellaoui, 2011; Charness and Viceisza, 2012).The most commonly used risk elicitation scales lie between 1 and 3 (Gandelman and Hernández-Murillo, 2015). Under Expected Utility, assumes that varying prices over the probability scale has no consequence as decision rules are linear in probabilities. Therefore, the use of a linear scale on risk attitude measurement is possible. But, if one uses nonlinear evaluation in probability to represent non-Expected Utility behaviours, the use of a linear probability scale can be problematic (Kahneman and Tversky, 1979). Moreover, the advanced risk elicitation measures are time-consuming and demand many cognitive skills to be with the respondents. As a result, they appear to be a less efficient method for obtaining direct measures of risk attitudes than" scale" procedures (Abdellaoui , 2011). On the other hand, responses to the same risk elicitation scale have shown differences among the rural and urban areas due to the differences in cognitive skills, income, and perception. Therefore, the study area has been identified as an important factor to be considered when designing the experiments for measuring risk aversion through scales (Dave *et al.,* 2010). For instance, it has been found that rural people have more convenience to understand and provide answers when directly asking their willingness-to-take risks (WTR) as a single question rather than the complex choice experiments or statements that use very similar explanations (Charness and Viceisza, 2012).

The CRRA function has been customized to match with farming systems and available data when estimating the EU. For instance, wealth estimates have been extracted as reported equity or land values (Jones *et al*., 2000). Consumption expenditure is widely used as the proxy for income in wealth measures in poor countries, but income is more widely used in high-income countries for this measure (Howe *et al*., 2009). Due to the perceived difficulties of calculating consumption expenditure; the wealth index has been proposed. In developed countries, wealth data are available and easy to capture. But, in developing countries, especially in rural areas, such data are not often readily available (Morris *et al*., 2000; Sumarto *et al*., 2007). Differentiation of people based on wealth indexes may not be meaningful when all most all the respondents are self-employed farmers or when few households only own the kinds of major consumer durables and assets. The self-reported total income is also subject to be biased due to the reluctance to reveal true information (Deaton, 1997; Morris *et al*., 2000; Montgomery *et al.,* 2000). Further, when individuals' incomes are measured in developing countries, the identification of multiple sources of income and changes that happened through time is important for accuracy. If there is any cost-free borrowing scheme available for consumption purposes, it is needed to be concerned as an income. But such borrowings are generally rare (Montgomery *et al*., 2000). However, it has proven the suitability of using income to measure wealth or financial success (Manun'ebo, 1994; Defo, 1994; Kannae and Pendleton, 1998). Sri Lankan context, the farmers do not have an equal distribution of collaterals or resources (Deininger and Sur, 2000; Edirisinghe, 2015). Sri Lankan farmers have barriers to finance and credit facilities, due to higher interest rates. Therefore, cost-free loans are rare (Shaw, 2004; Shoji *et al*., 2012).

Quasi-experiment:Difference in Difference method

Difference-in-Difference (DID) method is frequently used in impact evaluation studies as a quasi-experiment. DID is used, when randomization is not possible or keeping control groups is not practical due to ethical reasons or not feasible due to the nature of the measure i.e. weather information (Tall *et al*., 2018).The DID method compares the before and after performances of the control group and treatment group assuming, the interventions are happened as random and conditional on time and group effects (Bertrand and Mullainathan, 2004; Fredriksson and Oliveira, 2019). DID, estimates the treatment effect while accounting for the unobserved variables that are assumed to be remained fixed over time (Crown, 2014). In DID method, the key assumption is, the 'parallel trend' of groups which implies that in the absence of treatment, the average outcomes of the treatment group and the control group would follow parallel paths over time (Abadie,2005).

The DID method can be explained as, let Y (i,t) be the outcome of interest for the individual *i* at time *t*. The population is observed in a pre-treatment period t = 0, and in a post-treatment period t = 1. Between these two periods, the treatment is given to the treated group. Herein, Y_1 is the mean outcome in the period following the treatment and Y_0 is the mean outcome in the period prior to the treatment. In order to account for changes overtime, a control group is required. Assume, Group A, is administered the treatment between periods 0 and 1 (Let (YA_1 – YA_0) be the change in the treated group, while the control group B, does not receive the treatment at all, (YB_1 – YB_0) be the difference in the control group. Treated group denote D (i, t) = 1 if individual i has been exposed to the treatment before period t, D (i, t) = 0 otherwise. All those individuals with D (i, 1) = 1 treated, and those with D (i, 1) = 0 control (or untreated). Since individuals are only exposed to treatment after the first period, D (i, 0) = 0 for all i. The treatment effect ($\hat{\alpha}$) can be estimated using the DID estimate :{(Y_{A1} − Y_{A0}) -(Y_{B1} − Y_{B0})}. In the application, the DID estimation can be obtained by running a regression of Y_{it} on $T_{it,}$ t, and a dummy variable to represent the belonging group (Abadie,2005; Zhou *et al*., 2016). Based on this theoretical model, an empirical model was developed using paddy yields per hectare per farmer (Y) across the two cropping seasons as the dependent variable representing{($Y_{2017/18 \text{ treated}}$ − $Y_{2016/15 \text{ treated}}$) - ($Y_{2017/18 \text{ control}}$− $Y_{2016/15 \text{ control}}$)}in the theoretical model. The regression model (Eq (3) was used to estimate the absolute impact of the provision of weather information and changes that happened in the EU due to this intervention as the difference in the paddy yields. D_1 dummy variable used to represent the group where 1= treated group and otherwise zero. D_2 dummy variable used to represent the time periods, where 1= the year which provided information and otherwise zero. Therefore, D_2 equals 1 in 2017/18 and equals 0 in 2016/15. D_1D_2 is the interaction in between group and the time of treatment. $\beta_0 - \beta_3$ are coefficients. Where, $\beta_0$is the constant. $\beta_1$is the coefficient to group effect. The coefficient β_2 shows the trend over the treatment. The difference in paddy yields due to treatment is given by β_3 as the interaction of group and treatment. The regression equation has shown in below Eq(3)

Eq (3)

$$y = \beta_0 + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_1 D_2 + \epsilon_{it}$$

Data collection and use

The unit of analysis of the study was individual paddy farmers in Sri Lanka. The multi-stage random sampling technique was employed to select the sample of farmers. In the first stage, the entire farmer population was identified as distributed within four main paddy farming systems. They are namely, irrigated paddy farming system in the dry zone, Rain-fed paddy farming system in the intermediate zone(representing middle plains and the hill country), Rain-fed paddy farming system in the wet zone, and Rain-fed paddy farming system in the semi-arid regions(representing Eastern Coast and Southern Coast) of Sri Lanka. In the second stage, one district was selected within each farming system, and two Divisional Secretariat Divisions (DSD) from each selected district were selected randomly to carry out the research. Finally, a sample of 75 paddy farmers was selected from each DSD to make the whole sample size as 900. The selected districts were Anuradhapura (representing irrigated paddy farming system in the dry zone), Rathnapura (representing rain-fed paddy farming system in the wet zone), Badulla (representing rain-fed paddy farming intermediate zone- the hill country), Hambanthota (representing rain-fed paddy farming system in the semi-arid regions - Southern coast), Kurunegala (representing rain-fed paddy farming intermediate zone- middle plains), and Batticaloa (representing rain-fed paddy farming system in the semi-arid regions -Eastern coast).

One farming organization from each DSD from each district was kept as the control where, they did not receive any location specific rainfall information from the experts in the DOM. The control group was assumed to be used traditional knowledge or available general weather information given by agricultural officers or news media. Therefore, the control group had the opportunity to use weather information. Because it is not ethical or impossible to request refrain the use. Another farming organization was also selected from the other chosen DSD in each district as the treated group. The treated group was provided location specific rainfall information, especially designed for the study throughout the cultivation season in 2017/18 *maha* season as short-term, medium term and long term forecasts by considering the geographical area through the officers of the department of agriculture and the DOM. The 2016/17 *maha* season was not selected for the study due to research management reasons such as time requirement for establishing proper links with the farmers and community mobilization. And also, this cultivation season cannot be concerned as a typical cropping season since, it was impacted highly by the adverse weather conditions happened in the year (Groundviews, 2016; ReliefWeb, 2016). The provision of specific rainfall information was not random due to practical and ethical reasons. All farmers in the treated group were given this information. The received information utilization was completely on a voluntary basis. Both control group and the treated group consisted of 450 paddy farmers in each. The DSD areas for the control group and the treated group were located within a significant distance in each district where people have no significant connection to the farm decisions or agronomic practices. Thus, information sharing in-between the groups were assumed to be minimized. The baseline questionnaire survey was conducted to collect data before information provision in 2016. The end survey was conducted to collect the data after provision of specific rainfall information to the treated group in 2017/2018 *maha* season using the same pre-tested structured questionnaire of 2016.

The CRRA utility function was used to estimate the EU of weather information of paddy farmers as an ex –post-study in a quasi-experiment. The rainfall is considered as the major weather risk to paddy. The risk aversion of each sample was considered in three different levels as high (3), moderate (2), and low (1) in a simple risk elicitation scale. The average risk aversion values satisfied,$\varphi \neq 1$ condition in the CRRA utility function. The summation of household annual income of respondents was used to measure wealth (w) in two periods separately by considering all the earnings from both formal and informal income sources including transfer payments (like *Samurdhi* fund receiving*)* excluding the income from paddy. The net returns of all respondents for paddy (y) were estimated for 2016/15 *maha* season and 2017/18 *maha* season as the difference between the monetary value of the paddy harvest and the cost of production.

Even though randomization was used to select respondents and to establish control and treated groups, the true nature of the experiment is closer to a quasi-experiment. Because farmers of the control group had the access to general rainfall information, and also they were able to move within the district, they had the opportunity to meet agricultural officers in seasonal *kanna* meetings and use newly updated general scientific weather information. Not only that, but weather information is also like any other information type, where neither control over the spread nor a static resource. This specific behaviour created a difficulty of restricting the information use, providing information randomly or, isolate the users for treatments precisely (Jones *et al*., 2000; Msangi *et al*., 2006; Tall *et al*., 2018).Therefore, the rainfall forecasts were provided commonly to the all farmers in the treated group without any random selection or speciality. The paddy yields have resulted due to farmers' crop management decisions based on EU of weather information and the expected rainfall as an input. Therefore, the paddy yield per hectare per farmer of the two periods was collected to use as the dependent variable (y) in the DID regression model to estimate the absolute EU value of the provision of rainfall forecasts.

RESULTS AND DISCUSSION

The male representation of the whole sample was 80.22%. The average farming experience was reported as 13.1 years for the control group and 13.58 years for the treated group. Most of the respondents were full- time farmers in both groups. The age of the majority of farmers in both groups was in between 40-60 years. Therefore, it was observed a fairly large farming experience with them. The secondary education has been completed by the majority of the two groups. The paddy cultivation details, risk aversion, and the net returns of paddy of the two groups for the two periods have been compared using *t* statistics. The results are shown in Table 1.

Results revealed that, there were differences in the average cultivated land, average yield, and average net return for a farmer between the two groups in 2016 since $p<0.05$. The average wealth of a farmer, average paddy price, and average risk aversion had no

Table 1: The paddy cultivation details

	Baseline survey-before treatment (2015/16-Maha)			End survey - after treatment (2017/18-Maha)		
	Control group	Treated group	P	Control group	Treated Group	p
Average cultivated land (Ac)	2.45	2.06	0.00	1.98	2.24	0.03
Average yield (Kg/ha)	2872.71	2245.45	0.00	2738.44	3084.10	0.08
Average net return for a farmer	22895.93	20010.36	0.00	28487.72	38637.22	0.50
Average wealth of a farmer (LKR)	282680	280420	0.99	378462.4	284590.6	0.69
Average paddy price (kg)	30.81	30.54	0.48	35.51	36.64	0.00
Risk aversion	0.799	0.766	0.15	.85	.81	0.09

Table 2: Expected utility of climate information

	Control group	Treated group
Expected utility value of climate Information (EU)	3.61	4.37
Initial wealth(W_0) LKR	55,465,440.00	56,284,200.00
Wealth in 2018 (W) LKR	64,338,603.00	48,380,400.00
Risk aversion in 2018	0.85	0.81
Net return in 2018(y) LKR	9,942,912.75	16,707,117.25

differences in 2016. However, both groups have moved towards risk aversion in 2018 compared to 2016. But as expected from the provision of weather information, the average risk aversion of the treated group has shown a comparative significant reduction ($p<0.1$) in 2018. The net returns, which are based on the market prices were different ($p<0.05$) among the groups in 2016 but not in 2018. The results showed a significant difference in average cultivated lands ($p<0.05$) and the average yield ($p<0.1$) between the two groups in 2018. The estimated EU of two groups in 2018 has shown in Table 2.

The EU values do not symbolize monetary values, but according to derived EU values, the use of factors of crop production is determined (originally). The treated group has derived the highest EU and it is captured here using the CRRA. Therefore, the differences in paddy yields among the two groups can be used to examine the impact of the EU. The significant difference between variables of the two groups revealed that the randomization has not happened as a pure randomization. This validates the use of the DID regression method in analysing the impact of the EU.

DID regression results revealed that the provision of weather information (the treatment) to the treated group was significant ($p<0.05$), and the coefficient of the interaction was 960.54. This implies that paddy yields have improved by 960.54kg/ha per farmer in the treatment group due to the provision of weather information. Even though the r-square is low, it can be justified. The study is based on a psychological scale; therefore, measurement errors are possibly higher than the other studies. Not only that, by definition, it cannot predict that kind of psychological behaviour perfectly due to extant factors that are outside the control of researchers or scientific evidence and perhaps based on individuals' interpretations of whom they think they are (Schmidt and Hunter, 1996). Because, individuals are typically very heterogeneous by means of their attitudes, actions, and behaviours.

Therefore, lower r-square values also might add considerable value even though other unknown or immeasurable factors account for the majority of variation (Stefanski, 2000; Wansbeek and Meijer, 2001; Fuller, 2006). Due to that, a low r-square is not unusual in a psychological study, especially when analysing individual (not aggregated) data. Thus, low r-square values (below 1%) are generally accepted in various research models that deal with latent variables or psychology, i.e. Linear regression in psychological research, Structural equation models, Principal component analysis, and Measurement error models (Darlington, 1968; Cohen 1988; Cohen, 1992; Falk and Miller, 1992; Chin, 1998; Hair *et al*., 2011; Hair *et al.,* 2013; Van Tonder and Petzer, 2018). Therefore, a small r-square could have important implications (Cohen, 1988). For instance, the combination of other predictors mainly represents the modifiable behaviour and, only a small amount of the variance describes in the studied phenomenon. Knowing that limitation could be very important in future use since, it has been drawn through an empirical study (Onditi, 2013).

Not only that, low r-square values are common in longitudinal studies or cross-sectional studies. The use of secondary data achieves higher values for r-square than studies that use primary data and low sample sizes (Cohen, 1988; Itaoka, 2012). Further, modelling binary outcomes is exceedingly difficult to achieve high r-square values as the predicted probability values are not very likely to be exactly 1 and 0 (Rosenberg, 1988; Bollen *et al.,* 1995). Against this backdrop, the DID regression analysis in this research, has used dummy variables a lot. Further, the data collection method was primary and longitudinal; the number of regressors in the study, and the sample size was low. But corrected R-square values are barely reported due to the difficulty of using correction models (Yin and Fan, 2001; Roberts and Henson, 2002). Therefore, the research question and the size of the coefficient care about confounding, and careful evaluation of the model are much more important rather than just r-square. As a result, it needs to decide r- square practically with the research study and with the assumptions behind the analysis (Hair *et al*., 2010; Grace-Martin, 2012). Not only that low r-square means not a wrong model at all or poor accuracy of the analysing process (Onyutha, 2020). Further, some authors are highly against the usage of r-square. (Achen, 1982; Moksony and Heged,1990). But it is worth mentioning possible reasons for such a low r- square in the study as a clarification based on the facts (Itaoka, 2012).

Therefore, the observed yield gap can be explained, the farmers in the control group have reduced the cultivated land extents in the 2017/18 *maha* season due to the experienced climate change impacts in the previous year (2016 *maha*). This is justifiable, Sri Lanka experienced crop losses due to both floods and droughts in 2016 (Groundviews, 2016; ReliefWeb. 2016). Therefore, the control group was more risk-averse. This finding is similar to where it says people are generally risk-averse when the risk is sufficiently large and unknown (Arrow, 1971; Dillon and Scandizzo ,1978; Binswanger, 1981). However, the farmers in the treated group have moved a little bit towards low-risk aversion and have increased the cultivated land extents significantly due to the acquired precise weather information and derived high EU through it. This behaviour was found as similar to available literature, which explains the availability of information could result in low risk-aversion (Pope, 1982; Chavas, 1996; Br¨untrup, 2000; de Rouw, 2004). Higher initial wealth results in low-risk aversion generally (Hardaker *et al*., 2004). However, initial wealth status (2016) of the two groups was not statistically different and reported similar risk aversion values. Therefore, it is clear that the risk aversion has changed in the treated group in 2018 due to the provision of rainfall information. The accuracy of the provided weather information and the rational behaviour according to the derived EU, have supported the crop management activities as

Table 3: DID regression results

Model > F = 0.00		
R-squared = 0.15		
Adj R-squared = 0.13		
Variable	**Coefficient**	**P value**
Group	-626.52	0.000
Treatment	123.98	0.055
Interaction	960.55	0.000
Constant	2862.42	0.000

per the real weather patterns in the 2017/18 *maha* season. Thus, weather information has been impacted to reduce risk aversion and to face the reality.

As critics of this EU approach-based weather information valuation, decision-makers usually do not concern about the net profits over time but would concern about the year-to-year variability of returns or risks in decision making. Therefore, the decision maker's risk attitude is expected to impact the economic value placed on forecasts (Baquet *et al*., 1976; Byerlee and Anderson, 1982). Moreover, it is not necessary to have a positive correlation between risk aversion and the value of information. Because, if there is any additional occurrence of a bad event or a poor accurate measure, it would reduce the value of the forecasts. So, there is no monotonic relationship between the level of risk aversion and the value of climate information (Hilton, 1981; Mjelde and Cochran, 1988).

CONCLUSIONS

The study has revealed the applicability of the EU approach in an ex-post quasi-experimental design to value weather information. The paddy farmers who used the specific weather forecasts have derived high expected utility due to the reduction of risk aversion. As a result, factors of crop production have been utilized with more confidence and obtained a high average paddy yield per acre per farmer. Due to the secondary data limitation at the micro-level related to this kind of comparison, the primary data has been used only for two seasons. Thus, further research is needed to validate the results while capturing the impacts of other variables such as price fluctuations, impacts of other inputs, and technology which could impact the net returns and yields. Not only that, the use of advanced risk elicitation tools is important to reduce measurement errors.

The impacts of future climate change will reduce the accuracy of traditional weather predictions. The use of scientific weather information along with the appropriate mitigation measures and management practices should be promoted to reduce the risk aversion in decision-making to support the full utilization of the resources. Therefore, investments in advanced weather forecasting are needed. Provision of weather information as an input, i.e. location specific information packages will help the proper utilization of factors of crop production and increase the outputs.

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