Exploring Farmers' Cooperation over Agricultural Mitigation and Adaptation to Climate Change: Integrating Evolutionary Game Theory and Discrete Choice Modelling

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Abstract

The existing and impending threats of climate change are ubiquitous and unequivocal. Whereas the threats of climate change are experienced by a number of sectors directly and indirectly, these threats are more prominent for the agriculture sector. The significantly higher vulnerability of agriculture to climate change triggers serious challenges for food security and the long-term development of multiple nations. The looming intensification of climate change in the foreseeable future is expected to amplify the aforementioned challenges, and therefore, addressing these challenges with opportune and effective countermeasures is the call of the hour. Existing literature identifies mitigation and adaptation as the most effective countermeasures in addressing the escalated vulnerability of agriculture to climate change. The effectiveness of agricultural mitigation and adaptation to climate change depends upon strategic interactions among multiple stakeholders, starting from farmers to policymakers. However, strategic interaction among farmers is instrumental in shaping farm-level mitigation and adaptation, especially since they are the final decision-makers regarding the adoption of mitigation or adaptation measures. Coordination and cooperation among farmers may eliminate the potential free-riding issues induced by the public good characteristics of agricultural mitigation. In contrast, farmers' cooperation can potentially reduce the overall costs associated with adaptation, ensuring higher profitability. This study underscores the significance of farmers' cooperation and develops a game-theoretic model to investigate how farmers' cooperation over farm-level mitigation and adaptation evolves over time. The theoretical investigation elucidates the critical role of relative costs and benefits in determining the stability of farmers' cooperation over mitigation and adaptation. The investigation further highlights the significance of higher-order punishments in disincentivising non-cooperation and encouraging strategic resource and information exchange among farmers to cut down adaptation costs. The study further employs Probit regression models to analyse survey data and examine whether they align with the theoretically derived conditions underpinning farmers' cooperation. The empirical analysis also emphasises the role of farmers' risk preferences along with several other factors in influencing their decisions to adopt technologies based on mitigation and adaptation. The estimated probit regression coefficients are observed to be in accordance with the theoretical conditions. The estimated coefficients also reveal that farmers' investment in mitigation practices is significantly influenced by their willingness to take risks and access to credit. In contrast, farmers' access to extension services, per capita household income and perceptions regarding climate change are estimated to be the significant factors determining farmers' adaptation. The findings of this study have critical policy implications towards promoting widespread agricultural mitigation and adaptation, which is expected to address the profound challenges driven by the elevated vulnerability of the sector to climate change.

1 Introduction

Agriculture has been considered one of the most vulnerable sectors to climate change (Rao et al., 2019). Existing literature considers adaptation and mitigation as the most effective strategies in addressing the higher vulnerability of agriculture to climate change (Klein et al., 2005). Adaptation in agriculture incorporates all the activities that aim to reduce the intensity of negative impacts of climate change on the sector. Adopting different adaptive strategies minimises the adverse climatic impacts on agricultural systems and, therefore, is critical for promoting food security and sustainable development. Agricultural adaptation includes several strategies, such as building drainage facilities to mitigate water-logging issues, investing in irrigation infrastructure to mitigate drought issues, cropping different varieties of a single crop or multiple crops to reduce the magnitude of crop loss, etc. Agricultural adaptation strategies may subsume significant complementarities and substitutabilities (Bahinipati and Venkatachalam, 2015). In addition, the adaptation strategies involve coordinated action of multiple stakeholders, including the farmers, local governments, enterprises, etc. (Sun et al., 2023b).

In contrast, agricultural mitigation refers to minimising the emissions from agriculture and thereby damping the intensity or rate of climate change (Auerswald et al., 2018). Agriculture and allied land-use activities are responsible for one-fourth of carbon dioxide and half of methane emissions per annum due to several anthropogenic activities (Chataut et al., 2023). Growing cultivation of bioenergy crops is another predominant source of agricultural emission of N_2O, and this emission is expected to significantly increase in the coming years, especially given the incentives to these crops (Krol et al., 2019). The global mitigation potential from agriculture[1] has been estimated to be 5500 - 6000 million tonnes of equivalent per year by 2030 (Smith and Olesen, 2010). Agricultural mitigation strategies also have the potential to enhance resource use efficiency and establish a synergistic relationship between food security and rural development (Ogle et al., 2009). Therefore, mitigating emissions from agriculture is also crucial for addressing the link between climate change and agriculture.

Although different adaptation and mitigation strategies can potentially address the higher vulnerability of agriculture to climate change, none of them is universally applicable (Smith

[1]This estimate excludes the offsetting of fossil fuel by bio-energy.

and Olesen, 2010). Therefore, the synergies between both types of measures must be carefully evaluated to maximize their effectiveness (Smith and Wollenberg, 2013). Realizing the maximum potential of mitigation and adaptation is subject to enhanced collaboration among all stakeholders while safeguarding their mutual interests. Agricultural mitigation and adaptation involves the interaction of a number of stakeholders, including the farmers, policymakers, input suppliers, extension agents, financial intermediaries, etc. However, the behaviour of the farmers is the most prominent factor in agricultural mitigation and adaptation since they have to make the final decision regarding the adoption of new technologies.

Existing literature highlights the significant influence of farmers' behaviour on the adoption of different climate change mitigation and adaptation strategies (Tong et al., 2019). Farmers' mitigation behaviour is influenced by concerns regarding global climate change, whereas their adaptation behaviour is influenced by local concerns based on past climatic experience (Niles et al., 2015). The effectiveness of mitigation and adaptation is subject to the uncertainties associated with the rate of climate change. Given these uncertainties, the farmers may avoid adopting new adaptation and mitigation technologies.[2]

Farmers' decision to adapt has been estimated to be constrained by poor access to formal credit, extension services, weather information, lack of climate awareness (Akhtar et al., 2018), high input costs, land tenure issues, poor agricultural programs (Otitoju and Enete, 2016) and other institutional constraints. Similarly, farm-level mitigation is constrained by high input costs, poor access to physical and human capital, larger opportunity costs associated with adopting new technologies (Dulal et al., 2011), inadequate government support, and lack of access to extension services (Sánchez et al., 2016). The higher concentration of small and marginal farmers in developing states and the associated resource constraints also significantly inhibit farmers' adoption of mitigation and adaptation practices (Kropf and Mitter, 2022). Given this negative role of resource constraints, cooperation among the farmers is critical to the effective adoption of mitigation and adaptation strategies (Huq et al., 2004; Akhtar et al., 2018).

Furthermore, considering the large number of constraints outlined above, the widespread adoption of mitigation and adaptation strategies is subject to well-structured policy support. Analyzing the mechanism of farm-level adoption is imperative to formulating such sound policy measures. Existing literature analyzing farm-level mitigation and adaptation has been largely confined to static analyses (Ayanlade et al., 2018), and therefore, it overlooks the relevance of dynamic comparative analysis addressing the role of different stakeholders of the game (Sun et al., 2023b). This study attempts to fill the above research gap by analyzing the dynamics of farmers' cooperation over farm-level mitigation and adaptation to climate change in the Indian state of Odisha. Cooperation is likely to be critical in addressing the potential influence of farmers' poor resource access on constraining their mitigation and adaptation in the state.

This study uses the evolutionary game theory to analyse the dynamics of farmers' cooperation. Evolutionary game theory offers sophisticated theoretical tools integrating concepts of evolutionary biology and game theory[3] (Friedman, 1991). Nevertheless, evolutionary game

[2]This type of behaviour aligns with the theory of behavioural bias, which explains that rational agents may avoid a change in behaviour if it is subject to both benefits and risks (Menapace et al., 2013; Sun et al., 2023b).

[3]Game theory models strategic interaction between different agents with predefined rewards for each

theory strays from the traditional game theory by assuming finite rationality and learning ability of the agents[4] (Ma, 2009). Therefore, evolutionary game theory has the potential to incorporate the adjustment in strategies through learning and imitating, which aligns with the farmers' behaviour over mitigation and adaptation to climate change[5]. Evolutionary game theory facilitates modelling the interaction of rational actors under uncertainty, where the actors adapt their strategies through learning and imitation (Wang et al., 2023). Furthermore, evolutionary game theory is a good candidate for exploring the dynamics of interpersonal cooperation and agents' strategic behaviour with social interaction.

The solution concept of evolutionary game theory is characterized as the evolutionarily stable strategy, which was first introduced by Smith and Price (1973) to show how equilibrium and stability of a population are affected over a time period when some small number of mutants invade the population (Babu and Mohan, 2018). Evolutionary game theory and evolutionarily stable strategy were originally formulated as refinements of Nash equilibrium and designed for pairwise interaction among agents in a large population. However, later, the generalized version (Schaffer, 1988) was introduced, assuming a finite population and varying contest size. Evolutionary game theory has been used in multiple fields, including supply chain management (Babu and Mohan, 2018), trust-building and cooperation dynamic in software engineering industry (Wang and Redmiles, 2016), industrial policy (Sun et al., 2023a), pesticide regulation in agriculture (Gong et al., 2023), technology adoption in agriculture (Wu and Ma, 2020) etc. There have been some recent contributions on using evolutionary game theory to stakeholders' interaction over agricultural adaptations (Sun et al., 2023b). However, the theory has yet to be applied to farm-level mitigation of climate change. Furthermore, most of the existing studies do not incorporate empirical investigations to justify the theoretical findings. Addressing these research gaps, this study adopts evolutionary game theory to investigate how strategic interaction among the farmers will enhance their cooperation over mitigation and adaptation to climate change. The study further carries out an empirical analysis to validate the theoretical investigation.

The rest of this study is organized as follows. The next section defines the problem, introduces the model, outlines the assumptions and analyzes the model to derive the equilibrium conditions. Section 5.3 presents the data and methodology used in the empirical analysis, and the findings of the empirical estimations are discussed in Section 5.4. Finally, section 5.5 concludes the study.

2 Model design

The study assumes a large population of farmers where the farmers strategically interact within pairs and the payoff of each farmer is defined according to the interaction. The interaction between two farmers is formulated in terms of cooperation or non-cooperation

agent (Babu and Mohan, 2018). The sophisticated tools of game theory facilitate modelling single-shot or repeated interactions among the agents over finite or infinite time horizons.

[4]Traditional game theory assumes the agents to be perfectly rational.

[5]The farmers' behaviour aligns with the assumptions of bounded rationality (Tian et al., 2022; Sun et al., 2021); since they adapt and update their strategies through the process of trial and error (Sun et al., 2023b).

over farm-level mitigation and adaptation. Since farm-level mitigation of climate change targets to minimise agricultural emissions, it is considered a kind of contribution to the public good. Accordingly, there is a scope for cooperation among the farmers to eliminate free-riding issues (Panchanathan and Boyd, 2004; Shinada and Yamagishi, 2007). Farmers' adaptation to climate change may be considered as a private good. Nevertheless, the farmers have the option to coordinate and reduce the cost of adaptation (Alpizar et al., 2011). The farmers, in pairs, adjust their strategies relative to the changes in strategies of their respective counterparts. This strategy adjustment eventually generates an equilibrium known as the evolutionarily stable equilibrium. Each strategy in the strategy pair that generates the evolutionarily stable equilibrium is known as an evolutionarily stable strategy. The payoffs associated with the evolutionarily stable strategy are higher than average (Motlogh et al., 2021).

As mentioned below, several assumptions are constructed to formulate the model based on real-life scenarios.

2.1 Assumptions

1. The study assumes a one-population game where interaction happens between two farmers. The interaction is repeated multiple times, and all the two-farmer interactions are similar in structure.

2. The large population of farmers is homogeneous in every aspect at the outset of the game. It implies that the farmers are endowed with an equal amount of resources (Y), out of which they invest a certain amount in climate change mitigation (m) and adaptation (a).

3. Investing in mitigation and adaptation incurs cost $c(m)$ and $k(a)$, respectively, where the cost functions are twice differentiable and convex in nature.

4. Each farmer faces a damage cost due to climate change (D). The severity or intensity of the damage cost (δ) can be reduced by investing in mitigation and adaptation.

5. The farmers are rational agents who adjust their strategies through repeated interactions. Adjustment in strategies comes through farmers' imitation and learning from their counterparts.

6. The study assumes that the farmers' strategic interaction happens over different stages. In the first stage, each farmer has an option to either invest or not invest in mitigation. If both farmers in the pair invest in mitigation, damage costs can be reduced significantly.

7. In the next stage, the farmers have the option to invest in adaptation or not. Investing in mitigation and adaptation further reduces the damage cost, but the farmers can enjoy the benefits of adaptation privately.

8. In the third stage, the farmers have the option to cooperate with their counterparts by sharing resources and information. This cooperation can reduce the cost of adaptation and, hence, the total cost of each farmer.

With these assumptions, the game is modelled in three stages and explained as follows.

2.2 Stage 1: Investment in mitigation

The study assumes that in stage 1, the farmers can adopt two strategies, such as to invest in farm-level mitigation or not invest in mitigation. The proportion of farmers not investing in mitigation is ϵ, and the proportion of farmers investing in mitigation is 1 - ϵ. Since the game is formulated according to the evolutionary game theory, the strategy of not investing in mitigation can be considered a mutant strategy, and the farmers adopting this strategy may be considered mutants. In lines of evolutionary game theory, it may be assumed that the initial population of farmers is investing in farm-level mitigation, whereas some farmers deviate (with a proportion $1 - \epsilon$) and stop investing. With this setting, evolutionary game theory states that if the strategy of investing in mitigation is evolutionarily stable, it will successfully resist the deviation by farmers to not investing. In other words, provided investing in mitigation is evolutionarily stable, all the farmers will eventually invest in mitigation, and the non-investors will be driven out of the population.

While formulating the game in different stages, it has been assumed that in the initial stage, the farmers invest in mitigation only and not in adaptation. Farmers' investment in adaptation comes at a later stage, where it is combined with earlier mitigation to further reduce catastrophic damage costs. Investing only in mitigation in the initial stage may arise for several reasons. First, given mitigation is a contribution to public good, unilateral advance in mitigation by one or more farmers may encourage other farmers to follow suit and adopt the unselfish behaviour (Auerswald et al., 2018). This behaviour will ensure a larger contribution to the public good of global emission reduction. Second, the adoption of mitigation strategies is generally associated with lower upfront costs relative to adaptive measures. This lower cost may encourage the farmers to invest in mitigation in the initial stage, especially given the uncertainties subject to the effectiveness of these measures (see section 1). The uncertainties may also encourage the farmers to avoid adaptation and choose mitigation so that the rate of climate change can be reduced[6]. The benefits of mitigation measures may provide incentives for adaptation in a later stage. Third, the potential of mitigation in reducing the rate of climate change may make the farmers perceive it as a strategy to avoid future restrictions. These advantages may motivate the farmers to choose mitigation over adaptation initially.

With this argument, the model incorporating farmers' pairwise interaction over investment in mitigation is formulated and discussed as follows.

In stage 1, each farmers has a payoff function such as

$$\Pi_i = Y_i - c_i(m_i) - \delta^x D_i(m_{ij}) \tag{1}$$

where Π is the farmer's payoff defined over final wealth, Y is the initial wealth or resources, c is the cost function, m is the amount invested in mitigation, δ is the intensity of the damage cost due to climate change, x refers to different types of intensity and D is the associated damage cost function. Subscript i and j indicate the two farmers.

[6]As discussed in section 1, mitigation aims to reduce the rate of climate change by minimizing agricultural emissions.

The cost function $c(m)$ is assumed to be twice differentiable and convex in nature.

Therefore, $c_m = \frac{\partial c(m)}{\partial m} \geq 0$ and $c_{mm} = \frac{\partial^2 c(m)}{\partial m^2} > 0$.

Given the public good nature of mitigation, the magnitude of damage depends on the investment in mitigation by both farmers. Investment in mitigation affects the severity of damage δ. The damage cost is assumed to be decreasing with additional investment in mitigation, and there are decreasing returns from additional investment in mitigation. That means,

$D_m = \frac{\partial D}{\partial m} < 0$ and $D_{mm} = \frac{\partial^2 D}{\partial m^2} > 0$.

In stage 1, the producers have two pure strategies such as

S_m: the strategy in which the producer invests in mitigation

$S_{m'}$: the strategy in which the producer does not invest in mitigation

As mentioned earlier in this section, the proportion of farmers adopting strategy S_m is 1 - ϵ and the proportion of farmers adopting strategy $S_{m'}$ is ϵ. Given the assumption of pairwise interaction, a farmer who invests in mitigation (mitigation investor) is assumed to interact with a farmer who does not invest in mitigation (mitigation non-investor) with probability ϵ. Similarly, a mitigation investor interacts with another mitigation investor with probability $1 - \epsilon$. Table 1 shows the payoff function of farmers in a pair according to their strategies.

Table 1: Payoff matrix of farmers in stage 1

		Farmer 2	
	strategy type	S_m (1 - ϵ)	$S_{m'}$ (ϵ)
Farmer 1	S_m (1 - ϵ)	(Π_i^{mm}, Π_j^{mm})	$(\Pi_i^{mm'}, \Pi_j^{m'm})$
	S'_m (ϵ)	$(\Pi_i^{m'm}, \Pi_j^{mm'})$	$(\Pi_i^{m'm'}, \Pi_j^{m'm'})$

The interaction between two mitigation investors implies investment in mitigation by both farmers, which will increase total mitigation and reduce the severity of damage costs to δ^c. The associated damage cost function will be $\delta^c D_i(m_*)$, where m_* equals $m_i + m_j$. In contrast, the interaction between a mitigation investor and a non-investor will relatively increase the severity of damage to δ^b, and each farmer will face the damage cost function $\delta^b D_i(m_i)$, where i^{th} farmer invests in mitigation. Due to assumed symmetry of the game, $\delta^b D_i(m_i) = \delta^b D_j(m_i)$ and therefore there are chances of free-riding. The interaction between two non-investors will lead to the severity of damage cost to δ^a, and the associated cost function will be $\delta^a D_i(m_0)$. According to the severity of the damage,

$$\delta^a D_i(m_0) > \delta^b D_i(m_i) > \delta^c D_i(m_*).$$

With this specification, the expected payoff of non-investors is given by

$$E_{S_{m'}} = (1 - \epsilon)[Y_2 - \delta^b D_2(m_1)] + \epsilon[Y_2 - \delta^a D_2(m_0)] \tag{2}$$

where we denote the two farmers as farmer 1 and farmer 2. When the interaction between a mitigation investor and a non-investor happens, farmer 1 is assumed to invest in mitigation. In contrast, the expected payoff of investors is given by

$$E_{S_m} = (1-\epsilon)[Y_1 - c_1(m_1) - \delta^c D_1(m_*)] + \epsilon[Y_1 - c_1(m_1) - \delta^b D_1(m_1)] \tag{3}$$

The strategy of investing in mitigation will be evolutionarily stable when $E_{S_m} > E_{S_{m'}}$. That means when the expected payoff of the mitigation investors is greater than that of the non-investors, investing in mitigation will be an evolutionarily stable strategy.

Proposition 1: In a large population of farmers, investing in mitigation will be evolutionarily stable only when the cost of investment is smaller than the reduction in the climatic damage cost accrued to the mitigation.

Proof. According to the concept of evolutionary game theory, the strategy of investing in mitigation is evolutionarily stable only when ϵ is sufficiently small so that the invasion of the alternative strategy is resisted. Therefore, to check whether ϵ is sufficiently small, we proceed with the initial condition of stability:

$E_{S_m} > E_{S_{m'}}$,

which implies

$$(1-\epsilon)[Y_1 - c_1(m_1) - \delta^c D_1(m_*)] + \epsilon[Y_1 - c_1(m_1) - \delta^b D_1(m_1)]$$
$$> (1-\epsilon)[Y_2 - \delta^b D_2(m_1)] + \epsilon[Y_2 - \delta^a D_2(m_0)]$$

$$\implies Y_1 - c_1(m_1) - \delta^c D_1(m_*) - \epsilon Y_1 + \epsilon c_1(m_1) + \epsilon\delta^c D_1(m_*) + \epsilon Y_1 - \epsilon c_1(m_1) - \epsilon\delta^b D_1(m_1)]$$
$$> Y_2 - \delta^b D_2(m_1) - \epsilon Y_2 + \epsilon\delta^b D_2(m_1) + \epsilon Y_2 - \epsilon\delta^a D_2(m_0)$$

$$\implies -c_1(m_1) - \delta^c D_1(m_*) - \epsilon\delta^c D_1(m_*) - \epsilon\delta^b D_1(m_1)]$$
$$> -\delta^b D_2(m_1) + \epsilon\delta^b D_2(m_1) - \epsilon\delta^a D_1(m_0)$$

Under the condition of sufficiently smaller ϵ

$$-c_1(m_1) - D_1(m_*)[(1-\epsilon)\delta^c]$$
$$> -D_2(m_1)[(1-\epsilon)\delta^b]$$

Upon rearranging,

$$c_1(m_1) + D_1(m_*)[(1-\epsilon)\delta^c] < D_2(m_1)[(1-\epsilon)\delta^b]$$

$$\implies (1-\epsilon)[\delta^b D_2(m_1) - \delta^c D_1(m_*)] > c_1(m_1)$$

$$\implies -\epsilon > \frac{c_1(m_1)}{[\delta^b D_2(m_1) - \delta^c D_1(m_*)]} - 1$$

$$\implies \epsilon < 1 - \frac{c_1(m_1)}{[\delta^b D_2(m_1) - \delta^c D_1(m_*)]}$$

Now, ϵ is sufficiently small when $0 < \frac{c_1(m_1)}{[\delta^b D_2(m_1) - \delta^c D_1 m_*]} < 1$.

setting $\frac{c_1(m_1)}{[\delta^b D_2(m_1) - \delta^c D_1(m_*)]} > 0$ implies the cost $(c_1(m_1))$ is positive, which is an obvious condition.

In contrast, when, $\frac{c_1(m_1)}{[\delta^b D_2(m_1) - \delta^c D_1(m_*)]} < 1$,

it implies that

$c_1(m_1) < \delta^b D_2(m_1) - \delta^c D_1(m_*)$

Under the assumption of symmetry, the right-hand side of the above inequality implies the reduction in damage costs to the farmer who invests in the mitigation strategy. Therefore, the above condition means that investing in mitigation will be evolutionarily stable only when the cost of investment is less than the magnitude of reduction in climatic damage costs arising from the investment. In other words, investing in mitigation will be evolutionarily stable when the investment cost lies below the benefit obtained.

□

The above condition is in line with the usual decision-making process associated with a new investment where the costs and benefits are assessed, and the proposed investment is undertaken when the benefits exceed the costs. The advantages of mitigation measures in reducing the rate of climate change are likely to be reflected in the reduced damage costs and may be realized over longer time periods. Therefore, the cumulative decrease in damage costs may exceed the investment cost, satisfying the above condition. Provided the condition is satisfied, farmers not investing in mitigation measures will be driven out of the population, and the entire farmers' population will eventually invest in mitigation.

2.3 Stage 2: Investment in adaptation and mitigation

In stage 2, the entire farmers' population is assumed to be investing in mitigation initially. In other words, as per the proposition of the previous stage, stage 2 begins with the assumption that investing in mitigation is an evolutionarily stable strategy, and each farmer adopts mitigation measures. It is further assumed that the benefits of mitigation measures will encourage the farmers to invest in adaptation and further reduce the damage costs. Therefore, in stage 2, the farmers have an option to adopt two pure strategies, such as

S_a: the strategy in which the producer invests in adaptation

S'_a: the strategy in which the producer does not invest in adaptation.

The farmers who invest in adaptation combine it with earlier mitigation and experience a reduced intensity of damage cost (δ^d). In contrast, the farmers not investing in adaptation continue with mitigation only and experience comparatively higher damage costs (δ^c). It is assumed that the proportion of farmers adopting strategy S'_a is ϵ' and the proportion of farmers adopting strategy S_a is $1-\epsilon'$. Therefore, a farmer investing in adaptation interacts with another such farmer with probability $1-\epsilon'$ and with a farmer not investing in adaptation with probability ϵ'.

The payoff function incorporating farmers' pairwise interaction over investment in adaptation may be specified as:

$$\Pi_i = Y_i - c_i(m_i) - k_i(a_i) - \delta^x D_i(m_{ij}, a_i) \tag{4}$$

where k is the cost function and a is amount invested in adaptation. The cost function $k(a)$ is assumed to be twice differentiable and convex in nature. Therefore,

$k_a = \frac{\partial k(a)}{\partial a} \geq 0$ and $k_{aa} = \frac{\partial^2 k(a)}{\partial a^2} > 0$.

Since adaptation is a private good, the farmer investing in adaptation gets the private benefit in terms of reduced intensity of damage to δ^d, irrespective of the strategy of the counterpart. Similar to mitigation, the damage cost is assumed to be decreasing in additional investment in adaptation, and there are decreasing returns from additional investment in adaptation. That means,

$D_a = \frac{\partial D}{\partial a} < 0$ and $D_{aa} = \frac{\partial^2 D}{\partial m^2} > 0$.

Furthermore, according to the magnitude of the damage cost,

$\delta^a D_i(m_0) > \delta^b D_i(m_i) > \delta^c D_i(m_*) > \delta^d D_i(m_*, a_i)$.

Table 2 shows the payoff function of two farmers in pair according to their strategies of investing in adaptation and probability of interaction.

Table 2: Payoff matrix of farmers in stage 2

		Farmer 2	
	strategy type	S_a $(1 - \epsilon')$	$S_{a'}$ (ϵ')
Farmer 1	S_a $(1 - \epsilon')$	(Π_i^{aa}, Π_j^{aa})	$(\Pi_i^{aa'}, \Pi_j^{a'a})$
	$S_{a'}$ (ϵ')	$(\Pi_i^{a'a}, \Pi_j^{aa'})$	$(\Pi_i^{a'a'}, \Pi_j^{a'a'})$

With this specification, the expected payoff of the farmers adopting strategy S_a' is given by

$$E_{S_{a'}} = (1 - \epsilon')[Y_2 - c_2(m_2) - \delta^c D_2(m_*)] + \epsilon[Y_2 - c_2(m_2) - \delta^c D_2(m_*)] \quad (5)$$

In contrast, the the expected payoff of the farmers adopting strategy S_a is given by

$$E_{S_a} = (1-\epsilon')[Y_1 - c_1(m_1) - k_1(a_1) - \delta^d D_1(m_*, a_1)] + \epsilon'[Y_1 - c_1(m_1) - k_1(a_1) - \delta^d D_1(m_*, a_1)] \quad (6)$$

Proposition 2: In an environment with a large number of farmers, where the farmers are already investing in the mitigation of climate change, the strategy of investing in adaptation and combining adaptation with mitigation is evolutionarily stable when the relative increase in total investment cost is less than the relative decrease in the climatic damage cost accrued to combining mitigation and adaptation. In other words, combining adaptation with mitigation is evolutionarily stable when the total cost of investing in adaptation and mitigation is less than the total cost of investing only in mitigation (or not combining mitigation and adaptation).

Proof. The strategy S_a (investing in adaptation and mitigation) will be evolutionarily stable when

$E_{S_a} > E_{S_{a'}}$

which implies

$$\begin{aligned}
&(1 - \epsilon')[(Y_1 - c_1(m_1) - k_1(a_1) - \delta^d D_1(m_*, a_1)] + \epsilon'[Y_1 - c_1(m_1) - k_1(a_1) - \delta^d D_1(m_*, a_1)] \\
&\quad > (1 - \epsilon')[Y_2 - c_2(m_2) - \delta^c D_2(m_*)] + \epsilon'[Y_2 - c_2(m_2) - \delta^c D_2(m_*)] \\
&\implies Y_1 - c_1(m_1) - k_1(a_1) - \delta^d D_1(m_*, a_1) - \epsilon' Y_1 + \epsilon' c_1(m_1) + \epsilon' k_1(a_1) + \epsilon' \delta^d D_1(m_*, a_1) + \\
&\qquad \epsilon' Y_1 - \epsilon' c_1(m_1) - \epsilon' k_1(a_1) - \epsilon' \delta^d D_1(m_*, a_1) \\
&\quad > Y_2 - c_2(m_2) - \delta^c D_2(m_*) - \epsilon' Y_2 + \epsilon c_2(m_2) + \epsilon' \delta^c D_2(m_*) + \epsilon' Y_2 - \epsilon' c_2(m_2) - \\
&\qquad \epsilon' \delta^c D_2(m_*)
\end{aligned}$$

$$\implies Y_1 - c_1(m_1) - k_1(a_1) - \delta^d D_1(m_*, a_1)$$
$$> Y_2 - c_2(m_2) - \delta^c D_2(m_*) + \epsilon' \delta^c D_2(m_*) - \epsilon' \delta^c D_2(m_*)$$

$$\implies -c_1(m_1) - k_1(a_1) - \delta^d D_1(m_*, a_1)$$
$$> -c_2(m_2) - (1 - \epsilon')\delta^c D_2(m_*) - \epsilon' \delta^c D_2(m_*)$$

Assuming the probability of mutation to be sufficiently small,

$$(1 - \epsilon')\delta^c D_2(m_*) > c_1(m_1) + k_1(a_1) - c_2(m_2) + \delta^d D_1(m_*, a_1)$$

$$\implies 1 - \epsilon' > \frac{c_1(m_1)+k_1(a_1)-c_2(m_2)+\delta^d D_1(m_*,a_1)}{\delta^c D_2(m_*)}$$

$$\implies -\epsilon' > \frac{c_1(m_1)+k_1(a_1)-c_2(m_2)+\delta^d D_1(m_*,a_1)}{\delta^c D_2(m_*)} - 1$$

$$\implies \epsilon' < 1 - \frac{c_1(m_1)+k_1(a_1)+\delta^d D_1(m_*,a_1)-c_2(m_2)}{\delta^c D_2(m_*,a_2)}$$

The inequality will hold when

$$0 < \frac{c_1(m_1)+k_1(a_1)+\delta^d D_1(m_*,a_1)-c_2(m_2)}{\delta^c D_2(m_*)} < 1$$

$$\implies \frac{c_1(m_1)+k_1(a_1)+\delta^d D_1(m_*,a_1)-c_2(m_2)}{\delta^c D_2(m_*)} > 0$$

$$\implies c_1(m_1) + k_1(a_1) + \delta^d D_1(m_*, a_1) - c_2(m_2) > 0$$

$$\implies c_1(m_1) + k_1(a_1) + \delta^d D_1(m_*, a_1) > c_2(m_2)$$

In contrast,

$$\frac{c_1(m_1)+k_1(a_1)+\delta^d D_1(m_*,a_1)-c_2(m_2)}{\delta^c D_2(m_*)} < 1$$

$$\implies c_1(m_1) + k_1(a_1) + \delta^d D_1(m_*, a_1) - c_2(m_2) < \delta^c D_2(m_*)$$

$$\implies c_1(m_1) + k_1(a_1) + \delta^d D_1(m_*, a_1) < \delta^c D_2(m_*) + c_2(m_2)$$

$$\implies c_1(m_1) + k_1(a_1) - c_2(m_2) < \delta^c D_2(m_*) - \delta^d D_1(m_*, a_1)$$

□

The left-hand side of the above inequality indicates the difference in the costs between investing in mitigation and adaptation and investing only in mitigation. In contrast, the right-hand side shows the difference in climatic damage costs due to the two strategies. Therefore, when the relative increase in the cost of combining mitigation with adaptation is less than the associated relative decrease in climatic damage cost, the proportion of farmers not investing in adaptation will be driven out of the population. In other words, the entire farmers' population will invest in adaptation and mitigation.

2.4 Stage 3: Cooperation over adaptation

It is assumed that the entire population of farmers is initially investing in mitigation and adaptation in stage 3. However, there is an incentive for farmers to cooperate among themselves and reduce the cost of adaptation. The cooperation can be in terms of sharing inputs, information, experience, resources, etc. It can also take the form of joint investment in adaptation, which can significantly reduce the adoption cost for both farmers. Therefore, the farmers can experience the same damage cost $\delta^d D_i(m*, a_i)$ with a lower adoption cost $k_i^*(ac_i)$. Therefore, the farmers in stage 3 have two pure strategies, such as

S_c: the strategy in which the farmer cooperates with other farmers.

$S_{c'}$: The strategy in which the farmer does not cooperate with other farmers.

The study assumes the proportion of farmers not cooperating to be ϵ'' and the proportion of farmers cooperating to be $1 - \epsilon''$. Therefore, a cooperating farmer interacts with a non-cooperating farmer with probability ϵ'' and with another cooperating farmer with probability $1 - \epsilon''$.

The payoff function of a cooperating farmer can be specified as

$$\Pi_i = Y_i - c_i(m_i) - k_i^*(ac_i) - \delta^x D_i(m_*, ac_i) \tag{7}$$

where k^* is the cost function associated with the amount invested in adoption through cooperation and ac is the amount of investment in adaptation through cooperation. The cost function k^* is also assumed to be twice differentiable and convex in nature. Table 3 represents the farmers' payoff functions matrix according to their strategies.

Table 3: Payoff matrix of farmers in stage 3

		Farmer 2	
	strategy type	S_c (1 - ϵ'')	$S_{c'}$ (ϵ'')
Farmer 1	S_c (1 - ϵ'')	(Π_i^{cc}, Π_j^{cc})	$(\Pi_i^{cc'}, \Pi_j^{c'c})$
	S_c' (ϵ'')	$(\Pi_i^{c'c}, \Pi_j^{cc'})$	$(\Pi_i^{c'c'}, \Pi_j^{c'c'})$

The study assumes that one farmer takes the initiative towards cooperation by showing some signals, and the other farmer in the pair responds to it. A positive response implies that both farmers choose S_c, which reduces the cost of adaptation to $k_i(ac_i)$ for each. However, when the second farmer refuses to cooperate (and adopts $S_{c'}$), the respective farmer is assumed to face a punishment. It is assumed that the farmer who refuses to cooperate experiences a loss in reputation and may be refused cooperation by the respective counterpart in further interactions even when it changes decision and wishes to cooperate. Therefore, the farmer refusing to cooperate is assumed to bear an additional cost to the amount r, as a repercussion of the punishment. Although not directly, the above punishment mechanism may be considered as a form of social exclusion, which is considered a powerful strategy to promote cooperation (Sasaki and Uchida, 2013). Other 'costly punishments' discussed in the literature, such as taxes, fines and other penalties, can also be incorporated. However, we restrict the analysis to reputation loss exclusively.

Reputation loss can be safely assumed to be a punishment to the non-cooperating farmers and has the potential to stimulate cooperation. Reputation loss is assumed to drive down the relative position of the non-cooperating farmer in society. Relative position in society is highly valued by individuals (Gowda et al., 2021), and therefore, farmers may be discouraged from non-cooperating considering its negative impact on their relative social position. Furthermore, individuals are more likely to contribute when they are observed or monitored to do so (Henrich et al., 2006). Since the farmers' attitude towards cooperation is assumed to be observed by their counterparts, and it decides the probability of them being reciprocated through cooperation, it may motivate them to cooperate. Existing literature also argues that 'cooperation and punishment go hand-in-hand' (Henrich, 2006) and that individuals are more likely to sacrifice and contribute when assured of punishment to the non-cooperators.

Therefore, the payoff function of a non-cooperating farmer, incorporating the reputation loss when it interacts with a cooperating farmer can be specified as

$$\Pi_{S_{c'}} = Y_i - c_i(m_i) - k_i(ac_i') - \delta D_i(m_*, ac_i') - r \tag{8}$$

Based on the above discussion, the expected payoff of the farmers adopting $S_{c'}$ can be specified as

$$E_{S_{c'}} = (1-\epsilon'')[Y_2 - c_2(m_2) - k_2(ac_2') - \delta^d D_2(m_*, ac_2') - r] + \epsilon''[Y_2 - c_2(m_2) - k_2(ac_2') - \delta^d D_2(m_*, ac_2')] \tag{9}$$

Whereas the expected payoff of the farmers adopting S_c can be given by

$$E_{S_c} = (1-\epsilon'')[Y_1 - c_1(m_1) - k_1^*(ac_1) - \delta^d D_1(m_*, ac_1)] + \epsilon''[Y_1 - c_1(m_1) - k_1(a_1) - \delta^d D_1(m_*, a_1)] \tag{10}$$

Proposition 3: In a large farmers' population, where each farmer invests in climate change mitigation and adaptation, the strategy of cooperation among the farmers to reduce adaptation costs will be evolutionarily stable when the punishment to the non-cooperating farmers will sufficiently increase their total cost to a level higher than the total cost of the cooperating farmers.

Or, the punishment to the non-cooperating farmers will be sufficiently larger than the reduced adoption cost of the cooperating farmers.

Proof. The strategy S_c (cooperating with the other farmer will be an evolutionarily stable strategy when

$$E_{S_c} > E_{S_{c'}}$$

which implies

$$\begin{aligned}
&(1-\epsilon'')[Y_1 - c_1(m_1) - k_1^*(ac_1) - \delta^d D_1(m_*, ac_1)] + \epsilon''[Y_1 - c_1(m_1) - k_1(a_1) - \delta^d D_1(m_*, a_1)] \\
&\quad > (1-\epsilon'')[Y_2 - c_2(m_2) - k_2(ac_2') - \delta^d D_2(m_*, ac_2') - r] + \epsilon''[Y_2 - c_2(m_2) - k_2(ac_2') - \\
&\qquad \delta^d D_2(m_*, ac_2')]
\end{aligned}$$

$$\begin{aligned}
\implies\ & Y_1 - c_1(m_1) - k_1^*(ac_1) - \delta^d D_1(m_*, ac_1) - \epsilon'' Y_1 + \epsilon'' c_1(m_1) + \epsilon'' k_1^*(ac_1) + \epsilon'' \delta^d D_1(m_*, ac_1) + \\
&\quad \epsilon'' Y_1 - \epsilon'' c_1(m_1) - \epsilon'' k_1(a_1) - \epsilon'' \delta^d D_1(m_*, a_1) \\
&\quad > Y_2 - c_2(m_2) - k_2(ac_2') - \delta^d D_2(m_*, ac_2') - r - \epsilon'' Y_2 + \epsilon'' c_2(m_2) + \epsilon'' k_2(ac_2') + \\
&\quad \epsilon'' \delta^d D_2(m_*, ac_2') + \epsilon'' r + \epsilon'' Y_2 - \epsilon'' c_2(m_2) - \epsilon'' k_2(ac_2') - \epsilon'' \delta^d D_2(m_*, ac_2')
\end{aligned}$$

$$\begin{aligned}
\implies\ & Y_1 - c_1(m_1) - k_1^*(ac_1) - \delta^d D_1(m_*, ac_1) + \epsilon'' k_1^*(ac_1) - \epsilon'' k_1(a_1) \\
&\quad > Y_2 - c_2(m_2) - k_2(ac_2') - \delta^d D_2(m_*, ac_2') - r + \epsilon'' r
\end{aligned}$$

Under the condition of sufficiently small ϵ'',

$$\implies -c_1(m_1) - (1-\epsilon'')k_1^*(ac_1) - \delta^d D_1(m_*, ac_1) - \epsilon'' k_1(a_1)$$
$$> -c_2(m_2) - k_2(ac_2') - \delta^d D_2(m_*, ac_2') - (1-\epsilon'')r$$
$$\implies (1-\epsilon'')[r - k_1^*(ac_1)] > c_1(m_1) - c_2(m_2) - k_2(ac_2')$$

The cost function of the non-cooperating farmers is nothing but the cost function experienced by the farmers when the cooperation mechanism was absent (stage 2). In other words, the cost function of the non-cooperating farmers in stage 3 ($k_2(ac_2')$) and the general cost function of the farmers in stage 2 ($k_2(a_2)$) are the same. For simplicity, we replace the cost function of the non-cooperating farmers with $k_2(a_2)$ in the above inequality, such as

$$(1-\epsilon'')[r - k_1^*(ac_1)] > c_1(m_1) - c_2(m_2) - k_2(a_2)$$
$$\implies -\epsilon'' > \frac{c_1(m_1)-c_2(m_2)-k_2(a_2)}{r-k_1^*(ac_1)} - 1$$
$$\implies \epsilon'' < 1 - \frac{c_1(m_1)-c_2(m_2)-k_2(a_2)}{r-k_1^*(ac_1)}$$

When $\frac{c_1(m_1)-c_2(m_2)-k_2(a_2)}{r-k_1^*(ac_1)} < 1$, it implies that

$$c_1(m_1) - c_2(m_2) - k_2(a_2) + k_1^*(ac_1) < r$$

or $r > c_1(m_1) + k_1^*(ac_1) - c_2(m_2) - k_2(a_2)$

This inequality implies that the punishment to the non-cooperating farmers (r) should be large enough to compensate for the difference in total mitigation and adaptation costs of the cooperating farmers relative to the non-cooperating farmers.

The above inequality can also be represented as

$$c_1(m_1) + k_1^*(ac_1) < r + c_2(m_2) + k_2(a_2)$$

which implies that the total cost of cooperating farmers should be less than the total cost of non-cooperating farmers for the strategy of cooperation to be evolutionarily stable. In other words, the punishment for the non-cooperating farmers should be large enough to increase the total cost of non-cooperating farmers to a level higher than the total cost of cooperating farmers.

□

3 Empirical Analysis

This section empirically analyzes the above conditions using data collected through a survey. The data collection and empirical estimation are explained below.

3.1 Data

Cross-sectional data on 380 rice farmers are used to empirically analyse the conditions derived in the previous section. The data comprises a part of the broader survey conducted in three districts, namely, Cuttack, Kendrapara and Jajpur, from October 2021 to March 2022. The final sample of farmers, chosen through the multistage sampling approach, offers a good representation of the large farmers' population in the study area. Around 95 % of the agricultural landholdings in the surveyed area are small and marginal, whereas the proportion of small and marginal farmers in the sample is over 90 %. Small and marginal landholdings constitute around 86 % of the total agricultural landholdings in the study area, and around 93 % of the total farmers are small and marginal. Similarly, male farmers comprise around 75 % of our sample, whereas around 96 % of the cultivators in the study area are male[7]. Given the suitable representation, the empirical findings based on the sample farmers can be compared with the theoretical conditions. We enhance the comparison further by running the empirical estimations with and without district-fixed effects and the findings are presented accordingly.

3.2 Methodology

Proposition 1 states that the stability of farmers' investment in mitigation depends on the total costs associated with the investment and the benefits obtained in terms of reduction in the magnitude of the climatic damage costs. It implies that the relative costs and benefits associated with an investment in mitigation influence farmers' decision to invest in mitigation practices. This study employs the Probit regression model to estimate whether farmers' adoption of the mitigation measure is determined by the associated costs and benefits. The estimated Probit model can be specified by

$$D_i = \alpha_0 + \sum_{l=1}^{m} \alpha_l W_{il} + \epsilon_i \tag{11}$$

where D_i is a binary variable representing the adoption of mitigation measures by farmer i, D_i takes the value 1 if the farmer adopts mitigation practice, 0 otherwise. Farmers' mitigation in the study area mainly represents soil conservation measures that incorporate applying organic manure and increasing field bund heights. Applying organic manure reduces agricultural emissions (Aguilera et al., 2013) and reduces the runoff of toxic waste into water reservoirs.

The vector of explanatory variables, W, includes a variable $MitigationBen$, measuring farmers' perceived net benefits out of the adopted mitigation practice on a 7-point Likert scale. The farmers were explained about the net benefits associated with the mitigation practice and how it is influenced by the associated costs and actual benefits. Then, they were asked to rate their perception of net benefits out of mitigation practice on the 7-point scale mentioned above, starting from point 1 (strongly disagree) to point 7 (strongly agree)

[7] The subjects in our sample are the final decision makers in farming activities. In the absence of data on final decision makers in the three districts, we consider the data on the total cultivators, which are generally assumed to make the final decision.

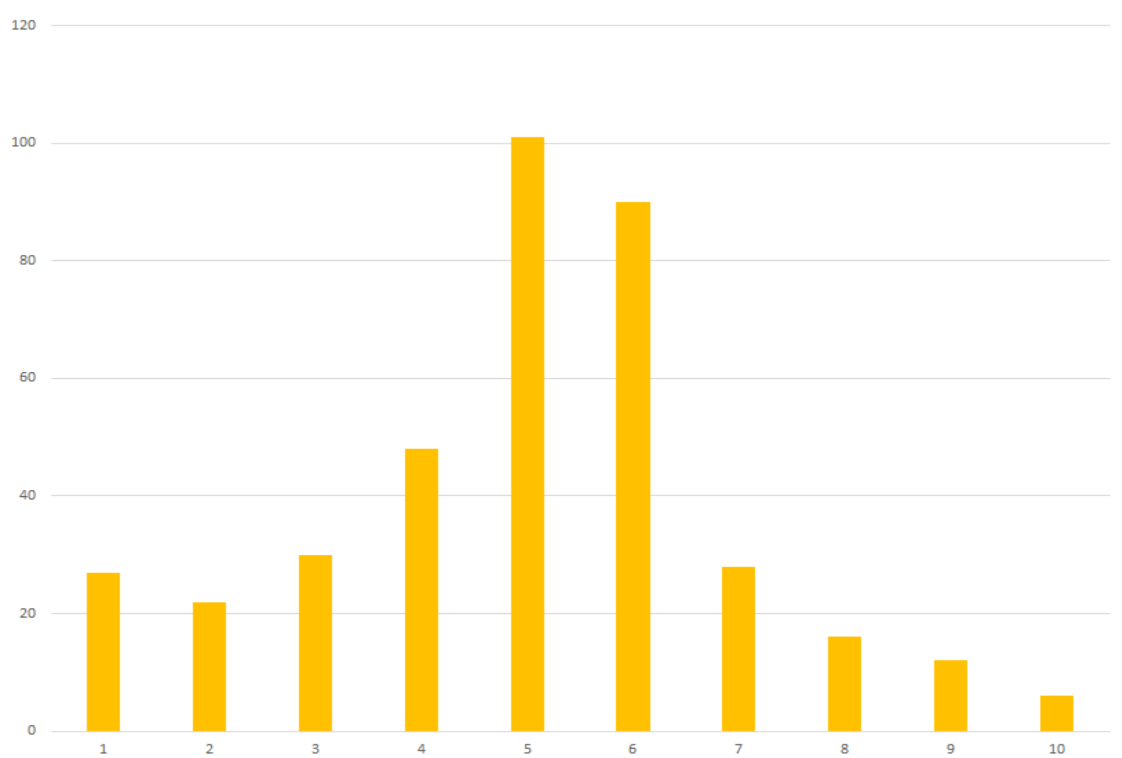

Figure 1: Frequency of risk preferences of the sample farmers
Source: Survey data

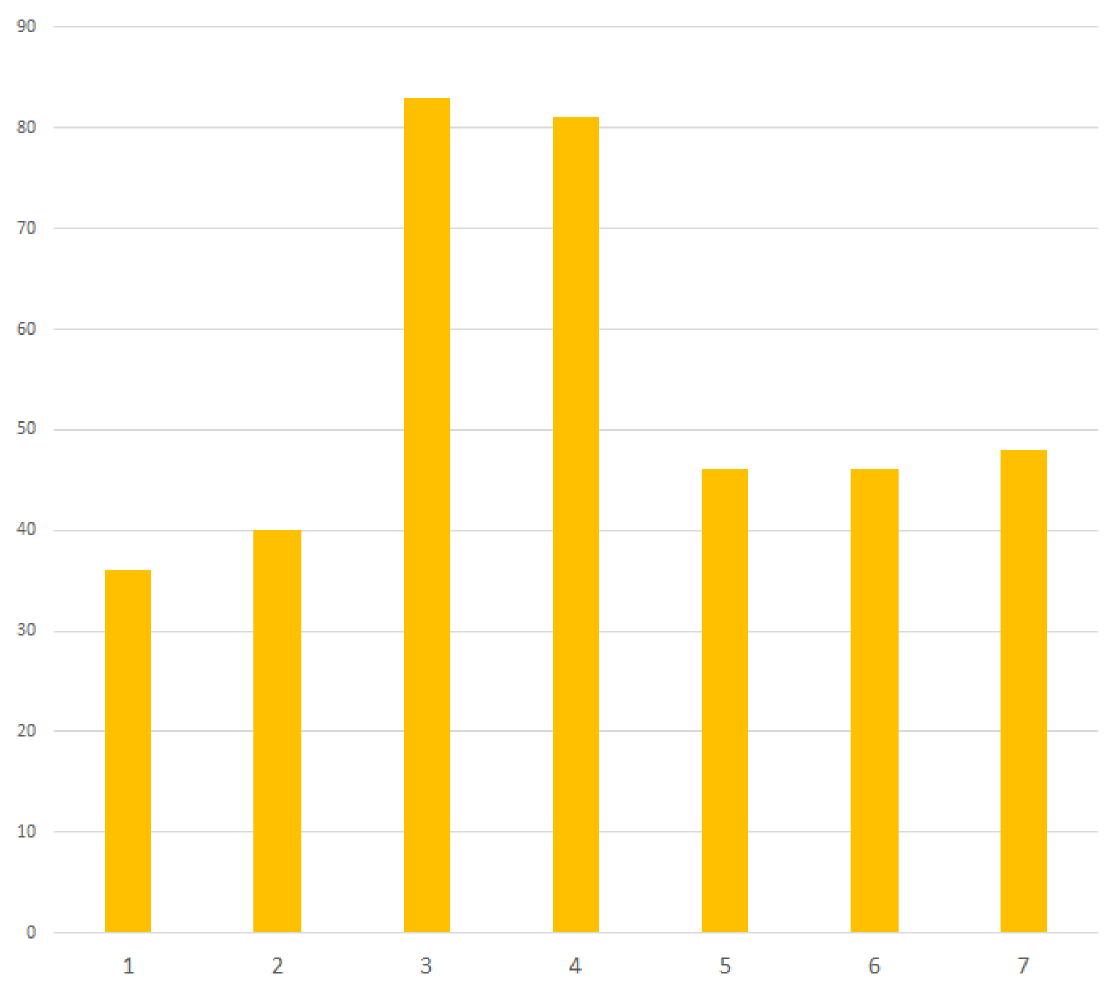

Figure 2: Frequency of $MitigationBen$
Source: Survey data

(Fig. **??**). The farmers' responses were cross-checked with additional questions. Fig. 1 shows the frequency of farmers' responses regarding the net benefit of mitigation measures. Table 4 shows the variables used in the estimation, whereas Table 5 presents their summary statistics.

Farmers' cooperation over adaptation is found to be evolutionarily stable when the cost incurred due to punishment is sufficiently large to increase the total cost of non-cooperating to a level higher than the total cost of cooperating. In other words, the farmers' cooperation in sharing information and resources regarding adaptation is determined by the magnitude of punishment to non-cooperators and the changes in the adaptation cost. We, therefore, use the Probit model given in Eq. 11 to estimate how costs of reputation loss and changes in adaptation costs influence farmers' cooperation over sharing resources and adaptation. Farmers' reputation loss, is measured on a 7-point Likert scale. The Likert scale is also used to measure farmers' perceptions of changes in their total costs due to cooperation and non-cooperation (Figs **??** and **??**). Fig. 3 shows the frequency of farmers' perceived increase ($CostIncrease$) and decrease ($CostReduce$) in adaptation costs. The measurement of farmers' perceptions on reputation loss is detailed below.

Literature differentiates between the direct and indirect effects of punishment on cooperation (Shinada and Yamagishi, 2007). The *direct effect* is realized when the threat of punishment stimulates cooperation. Therefore, under the direct effect, the fear of reputation loss and subsequent denial of cooperation from other farmers may motivate the non-cooperating farmers to cooperate. A 7-point Likert scale (Fig. **??**) was used to capture this direct effect, where the farmers were asked to rate their perception regarding the loss of their self-reputation in case they would not cooperate with other farmers. More specifically, the farmers were asked to rate the extent to which they perceive that they will cease to receive cooperation from other farmers once they refuse to do so. We, therefore, assume that the higher the point chosen on the scale, the larger the loss in self-reputation as perceived by the farmers. A larger loss in perceived self-reputation implies a higher-order punishment, which is hypothesized to increase the likelihood of farmers' cooperation over sharing resources and information. Fig. 4 represents the frequency of farmers' perceived self-reputation loss ($RepLossOwn$).

In contrast, the increased probability of cooperation under the threat of reputation loss may reassure the farmers seeking conditional cooperation that their cooperation effort will not be exploited by non-cooperating farmers. This reassurance may further enhance cooperation, which may be characterized as the *indirect effect* of punishment (Fehr and Gächter, 2002). This study follows Shinada and Yamagishi (2007) to define the farmers seeking conditional cooperation as willing to exchange information and resources only if their counterparts in the respective pair cooperate. We argue that the indirect effect of reputation loss also enhances farmers' cooperation and measure it on a 7-point Likert scale to estimate its influence separately (Fig. **??**). The farmers were asked to rate how much they perceived that they would stop cooperating with another farmer after that farmer denied their cooperation request. It is assumed that the higher the point chosen on the scale, the higher the perceived punishment to other farmers and the larger the likelihood of cooperation under the indirect effect. Fig 4 exhibits the frequency of perceived reputation loss of other farmers ($RepLossOthers$). The variables, $RepLossOwn$ and $RepLossOthers$, are used separately in the estimations to avoid multicollinearity issues.

However, the estimation of Eq. 11 poses the possibility of a selection bias. This bias may arise when the farmers choosing mitigation investments perceive higher net benefits. The probability of such selection bias may be larger for the actual adopters since their perceived net benefits may be based on their experiences out of mitigation measures. To this end, it could have been more appropriate restricting the sample to the non-adopters or the prospective adopters. However, the large sample is used to exploit its advantages in terms of enhancing the reliability and accuracy of the estimates. Therefore, we address the selection bias using the Two Step Bivariate Probit estimation (Morrissey et al., 2016). The estimation method is adapted to incorporate the effects of farmers' perceived benefits, reputation loss and changes in adaptation cost. To this end, the selection equation includes farmers' perceived net benefit while estimating the determinants of mitigation investment. In contrast, it includes the farmers' perceived reputation loss and changes in adaptation cost while estimating the determinants of farmers' cooperation over adaptation.

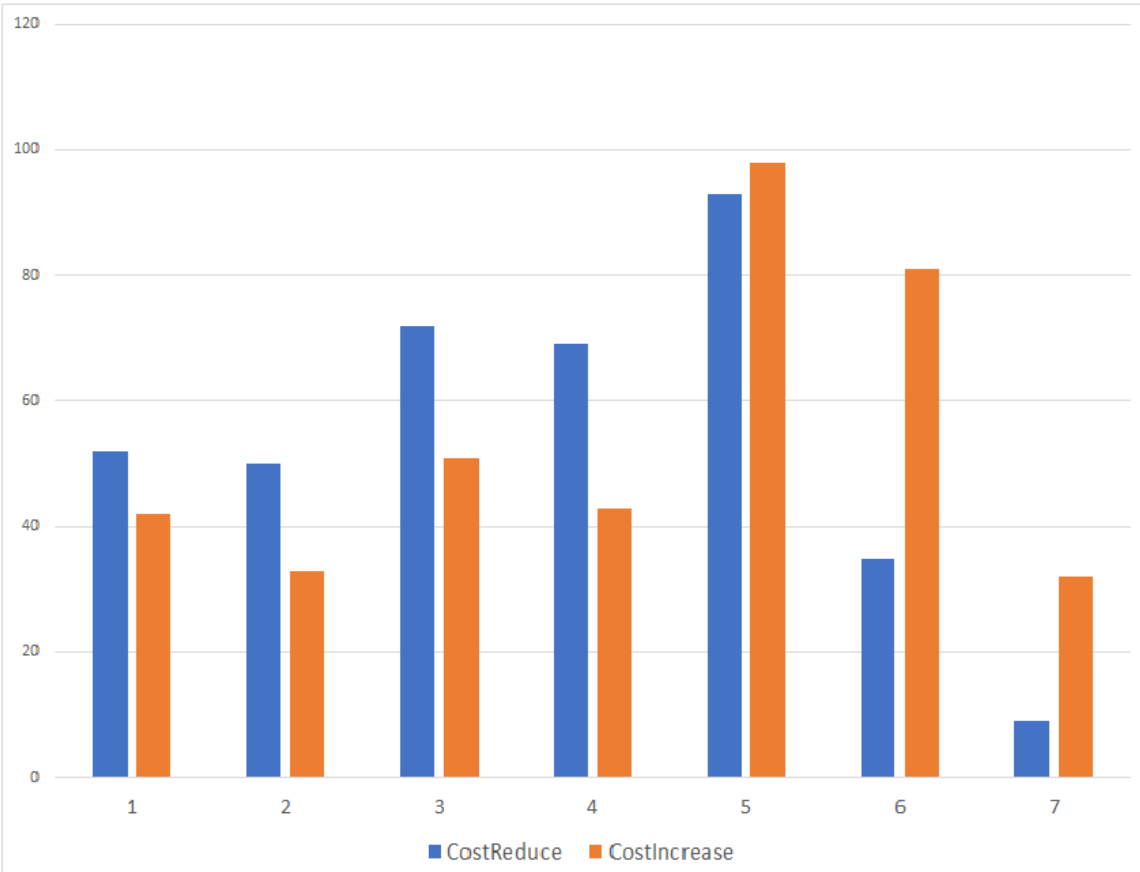

Figure 3: Frequency of $CostIncrease$ and $CostReduce$
Source: Survey data

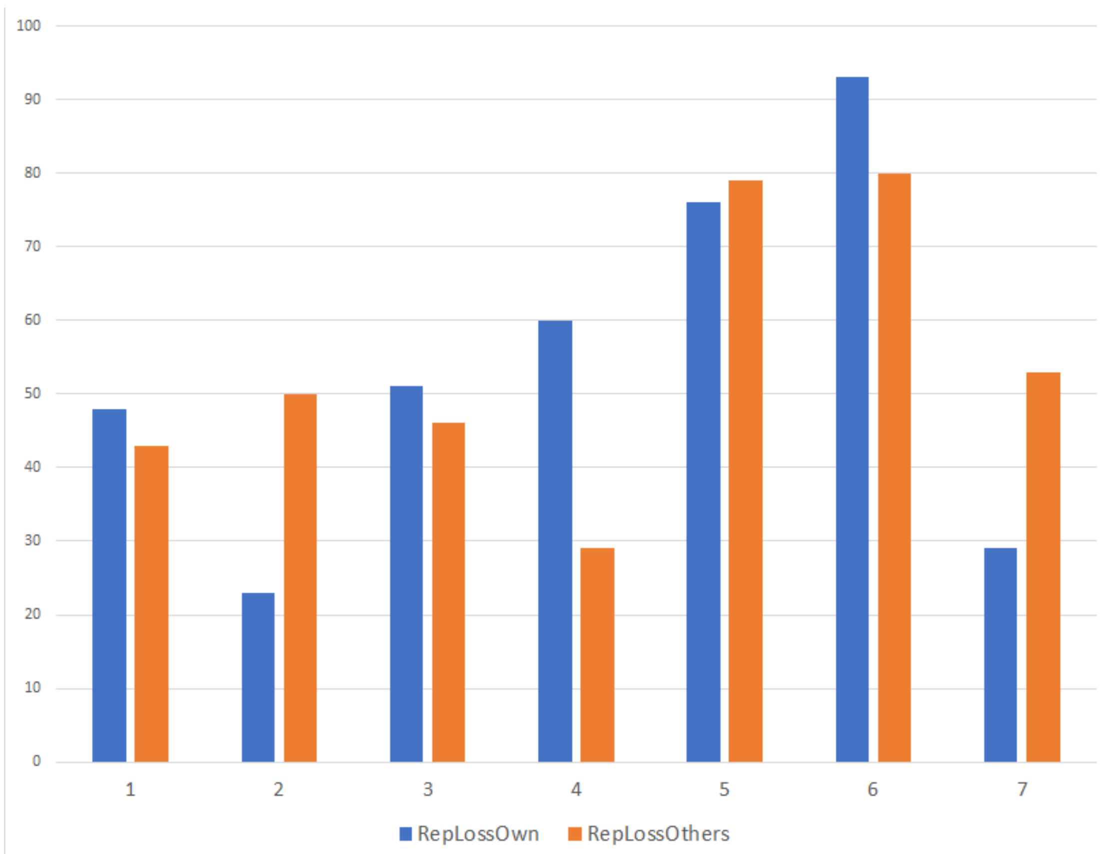

Figure 4: Frequency of *RepLossOwn* and *RepLossOthers*
Source: Survey data

Table 4: Description of variables

Variable	Description (Units in brackets)
Dependent variables	
Mitigation	1, if the farmer adopts mitigation measures, 0 otherwise
CooperationInf	1, if the farmer cooperates with others by sharing information related to adaptation
CooperationRes	1, if the farmer cooperates with others by sharing resources
Independent variables	
Risk preferences	Farmers' self-reported risk preferences (10-point scale)
MitigationBen	Farmers' perceived net benefit out of mitigation measures
CostReduce	Farmers' perceived reduction in adaptation cost
RepLossOwn	Farmers' perceived self reputation loss
RepLossOthers	Farmers' perceived reputation loss corresponding to other farmers
CostInc	Farmers' perceived increase in adaptation cost
Education	Farmers' level of education (year)
Information	1 if the farmer has access to weather information, 0 otherwise
Extension	1, if the farmer has accessed extension services, 0 otherwise
Credit	1 if the farmer has access to institutional credit, 0 otherwise
Log(Per Capita Income)	Logarithmic value of per capita household income (INR)
PerClim	Perception regarding Climate change (binary)
PerceptionLos	Perceived future crop loss due to climate change (percentage)

INR: Indian Rupee;

Table 5: Summary statistics of the variables

Variable	Mean	S. D.	Median	Min	Max
Dependent variables					
Mitigation	0.79	0.41	1	0	1
CooperationInf	0.73	0.45	1	0	1
CooperationRes	0.64	0.48	1	0	1
Independent variables					
Risk preferences	4.97	1.98	5	1	10
MitigationBen	4.03	1.80	4	1	7
CostReduce	3.64	1.63	4	1	7
RepLossOwn	4.28	1.82	5	1	7
RepLossOthers	4.32	1.97	5	1	7
CostIncrease	4.30	1.81	5	1	7
Education	6.87	3.97	7	0	15
Extension	0.35	0.49	0	0	1
Credit	0.48	0.50	0	0	1
Log(Per capita Income)	7.52	0.74	7.60	5.14	9.62
Perceived Loss	0.28	0.16	0.30	0.00	0.80
Perception	0.92	0.28	1	0	1

n = 380
Source: Survey data

4 Results of Empirical analysis

Table 6 shows the results of the estimated Probit model explaining the influence of different factors on farmers' decisions to invest in mitigation measures. As mentioned earlier, Table 6 reports the estimates with and without district fixed effects in the Probit regression model. The table shows that farmers' willingness to take higher risks increases the likelihood of investing in mitigation measures. In other words, the farmers who are not ready to take risks avoid investing in mitigation practices. This finding aligns with Jianjun et al., 2015 in terms of risk-averse farmers' attitudes in delaying or postponing technology adoption. This finding is also consistent with the propositions of the theory of behavioural bias, as explained in Section 1 (See footnote 1).

However, it is interesting to find that the likelihood of investing in mitigation reduces when the farmers have access to credit. Agricultural credit in the study area is usually of shorter periods. Therefore, the farmers availing credits are more likely to resort to more established practices, promising good short-term returns. In contrast, returns from mitigation practices, such as soil conservation, are realised over relatively longer periods. Therefore, the farmers availing credit may avoid investing in soil conservation and other mitigation measures. Another reason may also be that the farmers accessing credit may find the need to cooperate with other farmers less relevant. In other words, credit access may make the farmers self-dependent and act as a substitution for cooperation with others over investment

Table 6: Probit regression estimates: Investment in mitigation

	With district-fixed effects		Without district-fixed effects	
Variables	AME	S.E	AME	S.E
Intercept	-0.325	1.349	0.095***	1.019
Risk preferences	0.095***	0.075	0.096***	0.073
MitigationBen	0.071***	0.070	0.071	0.065
Education	-0.002	0.027	0.007	0.023
Extension	-0.051	0.194	-0.030	0.178
Credit	-0.078**	0.199	-0.070**	0.189
log(per capita income)	-0.028	0.158	-0.081	0.127
PerceptionLos	0.055	0.735	-0.012	0.733
PerClim	-0.068	0.373	-0.023	0.335
Kendrapara	0.158***	0.284		
Jajpur	0.210***	0.273		
AIC	257.23		276.42	
BIC	300.56		311.88	
Pseudo R^2	0.398		0.339	
Log likelihood	-117.61		-129.20	
LR χ^2	155.91		132.72	
Prob $> \chi^2$	< 0.01		< 0.01	

Source: Author's own work

in mitigation measures. This aligns with the findings of Mahapatra and Jena (2023) in terms of the negative impacts of crop and term loans on crop yields.

Table 6 further exhibits that an increase in farmers' perceived net benefit enhances investment in mitigation strategies. This finding is consistent with the conditions derived with reference to Proposition 1. It, therefore, implies that the farmers have to be empowered to maintain the cost of mitigation investment at a lower level so that net positive benefits can be realised. Subsidising farmers' investment in mitigation technologies can be a potent cost-reducing strategy. Other strategies may include providing conditional credits and other financial incentives for adopting mitigation measures. These incentives may be integrated with training programmes to upgrade farmers' knowledge on the benefits of mitigation measures, whereas farmers' access to mitigation technologies and advanced information should be enhanced for effective adoption. Effective adoption of mitigation practices should be ensured to maximise the benefits, especially since the benefits are realised in terms of reduced damage costs. Disseminating information about the advantages of coordinating and mutually investing in mitigation measures may further promote the adoption of mitigation measures. Promoting farmers' mutual investment appears to be the first step towards widespread adoption of mitigation measures, which may eventually address the larger agricultural mitigation potential of the study area and the state.

Table 7 shows that the probability of information exchange among farmers significantly increases with their higher willingness to take risks, when farmers' self-reputation loss is incorporated, and district-fixed effects are excluded. The positive impact of farmers' risk preferences on information exchange can be harnessed by targeting risk-tolerant farmers, leveraging their higher propensity to take risks for collective actions and circulating their success stories to motivate other farmers regarding how shared benefits can be stimulated by risk-taking. In addition, risk-sharing mechanisms may be promoted through group interactions, such as farmer groups, cooperative networks, group insurances, etc., which should be designed so that group or peer pressure can foster trust along with reciprocity. Such group-based or peer-influenced interactions may also foster institutionalising information exchange within socially visible frameworks, which may further contribute to incentivising information-sharing mechanisms. Since farmers' willingness to take higher risks increases the likelihood of information-sharing when district-fixed effects are excluded, it implies that district-fixed effects suppress the influence of farmers' risk preferences on the likelihood of information exchange. This finding implies that sharing attitude may have been moderated by local institutions and culture. Therefore, context-specific interventions targeting the districts whose performance is not impressive in stimulating peer cooperation should be planned and implemented.

However, willingness to take risks does not significantly influence farmers' information exchange in other instances. Table 8 exhibits that farmers' risk preferences are not significant determinants of their resource exchange. Farmers in the study area may be experiencing higher climate change-induced threats regardless of their risk tolerance levels, especially given the higher vulnerability of the study area to several climatic risks (see Section 3.1). The farmers may also value the benefits of sharing information and resources, and consider it a useful strategy in mitigating climatic risks, irrespective of their risk preferences.

Table 8 shows that the likelihood of farmers' cooperation in sharing resources also remains unaffected by their risk preferences. However, similar to information, the probability of resource sharing is significantly enhanced by farmers' perceived reputation loss, both of themselves and other farmers. Therefore, the direct and indirect effects of punishment are also likely to encourage resource-sharing among the farmers.

Table 7: Probit regression estimates: Cooperation over sharing information

	With district-fixed effects		Without district-fixed effects		With district-fixed effects		Without district-fixed effects	
Variables	AME	S.E	AME	S.E	AME	S.E.	AME	S.E
Intercept	-0.743***	1.428	-0.560***	1.269	-0.662***	1.557	-0.569***	1.478
Risk preferences	0.011	0.054	0.013*	0.055	0.006	0.055	0.007	0.058
CostReduce	0.081***	0.086	0.079***	0.075	0.055***	0.080	0.054***	0.067
Education	-0.003	0.026	-0.0002	0.025	-0.001	0.031	0.001	0.029
Extension	0.021	0.218	0.037	0.218	0.047	0.221	0.058*	0.223
Credit	-0.021	0.203	-0.014	0.203	-0.032	0.230	-0.027	0.223
log(per capita income)	0.012	0.143	-0.010	0.141	0.005	0.162	-0.006	0.152
PerceptionLos	0.155	0.750	0.107	0.745	0.107	0.760	0.074	0.792
PerClim	-0.109	0.438	-0.098	0.475	-0.013	0.558	-0.005	0.532
RepLossOwn	0.047***	0.058	0.047***	0.058				
RepLossOthers					0.056***	0.065	0.058***	0.065
CostIncrease	0.064***	0.066	0.070***	0.063	0.058***	0.066	0.061***	0.061
Kendrapara	0.100**	0.278			0.059	0.300		
Jajpur	0.101**	0.302			0.071*	0.343		
AIC	218.92		223.37		206.27		206.25	
BIC	270.14		266.71		257.48		249.59	
Pseudo R^2	0.56		0.54		0.59		0.58	
Log-likelihood	-96.459		-100.69		-90.132		-92.125	
LR χ^2	251.15		242.70		263.81		259.82	
Prob > χ^2	< 0.01		< 0.01		< 0.01		< 0.01	

Source: Author's own work

It is clear from the Probit regression estimates (Tables 7 and 8) that the likelihood of information and resource sharing significantly increases when there is an increase in farmers' perception of reputation loss of themselves and of other farmers. The likelihood-enhancing effect of both reputation-loss variables is robust to the exclusion of district-fixed effects. Therefore, Probit regression estimates gather evidence in favour of the direct and indirect effect of punishment, consistent with studies like Shinada and Yamagishi (2007). In other words, the findings of our empirical analysis underscore the potential of punishment in promoting widespread adaptation and validate the conditions corresponding to Proposition 3. This potential may be harnessed by designing formal penalty mechanisms for non-cooperators and providing social incentives, such as public recognition, honour and reputational gains to cooperators.

The effectiveness of reputation loss as a punishment is conditional on a good information-communication network. The information dissemination network can be strengthened by enhancing the quality and accessibility of extension services, and by promoting farmers' interactions within groups, cooperatives and other community-centric organisations. These interactions may also contribute to the emergence of trust among farmers, which is likely to be the cornerstone of cooperation among them. Trust-building may be enhanced further by spreading awareness and training the farmers, which points towards the crucial role of extension agents. Access to extension services may develop a collective understanding of climatic risks among the farmers. It may also help them identify the synergies among the adoption of multiple risk management practices and how it can be enhanced through resource sharing. Probit regression estimates show that farmers having access to extension services are more likely to share information (Table 7) and resources (Table 8) when they perceive a loss in fellow farmers' reputation and when district-specific unobserved effects are omitted. Existing literature highlights farmers' poor access to extension services in coastal Odisha (Bahinipati, 2015), and therefore, the access should be improved to leverage its positive impact on information and resource exchange. Promoting community-based extension education, with a special focus on enhancing information and resource exchange among the farmers may be adopted

Table 7 also shows that farmers who perceive that cooperation reduces the cost of adaptation are more likely to share information with others. Farmers' likelihood of information sharing is also enhanced by their perceptions regarding the higher costs associated with non-cooperation, and the significance of both variables remains robust to the omission of district-fixed effects. Table 8 further shows that farmers who perceive non-cooperation increases adaptation cost and cooperation reduces it, are more likely to exchange resources. The significant influence of the cost and reputation loss variables on farmers' cooperation over information and resource exchange validates the conditions derived with reference to Proposition 3. The positive and significant influence of both cost variables on farmers' resource and information sharing warrants equipping farmers with effective cost-sharing mechanisms. Fostering trust through group and community-based interactions can contribute to reducing perceived costs. Further provisions may include subsidies, micro-grants, conditional credits, discounted credit interest, etc., to early cooperators. In addition, farmers' access to weather and crop-related information, resources, advanced mitigation and adaptation technologies, etc., should be upgraded. Finally, examples of successful resource and information sharing and its cost-reducing effect may be circulated among the farmers to incentivise cooperation.

Table 8: Probit regression estimates: Cooperation over sharing resources

	With district-fixed effects		Without district-fixed effects		With district-fixed effects		Without district-fixed effects	
Variables	AME	S.E	AME	S.E	AME	S.E.	AME	S.E
Intercept	-1.137***	1.096	-1.011***	0.990	-1.070***	1.178	-1.096***	1.065
Risk preferences	-0.0002	0.040	0.001	0.040	-0.005	0.042	-0.003	0.040
CostReduce	0.055***	0.050	0.055***	0.049	-0.003	0.066	-0.001	0.059
Education	-0.002	0.020	-0.002	0.019	0.0007	0.025	-0.0009	0.023
Extension	0.064	0.169	0.059	0.166	0.092**	0.203	0.085**	0.201
Credit	0.014	0.158	0.012	0.156	0.012	0.183	0.008	0.181
log(per capita income)	0.047	0.119	0.031	0.107	0.049*	0.132	0.051**	0.115
PerceptionLos	-0.137	0.561	-0.152	0.559	-0.183	0.699	-0.177	0.682
PerClim	0.089	0.315	0.093	0.314	0.156**	0.279	0.149**	0.273
RepLossOwn	0.060***	0.044	0.059***	0.043				
RepLossOthers					0.107***	0.059	0.107***	0.058
CostIncrease	0.084***	0.046	0.085***	0.045	0.060***	0.057	0.060***	0.056
Kendrapara	0.063	0.215			-0.009	0.225		
Jajpur	0.0001	0.216			-0.049	0.281		
AIC	374.93		372.81		286.58		283.98	
BIC	426.15		416.14		337.79		327.31	
Pseudo R^2	0.29		0.29		0.47		0.47	
Log-likelihood	-174.47		-175.40		-130.29		-130.99	
LR χ^2	149.03		147.16		237.39		235.99	
Prob $> \chi^2$	< 0.01		< 0.01		< 0.01		< 0.01	

Source: Author's own work

However, 8 shows that the farmers who perceive to have experienced changing climatic conditions are more likely to share resources. The farmers perceiving changes in climatic conditions must have been aware of the exorbitant damage costs and may recognize the importance of resource sharing to facilitate adaptation and reduce the costs. Given this advantageous role of perception regarding changing climatic conditions, farmers' knowledge and awareness of climate change and its hazardous effects should be improved. Organising awareness campaigns, training programs and providing qualitative extension services may enhance farmers' understanding of the adversities associated with climate change and encourage them to opt for adaptive practices and reduce their costs by trading resources.

An increase in the per capita household income encourages farmers to share resources. An increase in income may positively affect farmers' access to resources and encourage farmers to invest in modern technologies, which may not always be readily accessible to them. Therefore, these farmers may consider exchanging resources and undertaking collective investment for improved access to innovative technologies. Nevertheless, the lack of significant influence of access to extension services on the adoption of different practices, indicates a possibility of an implementation gap that has to be explored and addressed.

5 Conclusion

The effectiveness of mitigation and adaptation in addressing the higher vulnerability of agriculture to climate change is widely acknowledged. Although widespread mitigation and adaptation are highly desirable for the developing nations due to their higher climatic vulnerability, these nations often face the trade-off between investing in agricultural mitigation-adaptation and maintaining the agricultural growth rate. Therefore, designing appropriate measures to promote agricultural mitigation and adaptation, in addition to maintaining the agricultural growth rate, stands atop the policy priorities of these nations. Farmers' behaviour and strategic interaction are central to the promotion of mitigation and adaptation, since they make the ultimate decision on adopting these technologies. Addressing the gaps in existing research in terms of not analysing the dynamics of farmers' strategic interaction, this study offers a novel approach to model farmers' strategic interaction over mitigation and adaptation using evolutionary game theory. More specifically, this study employs evolutionary game theory to model farmers' interaction and cooperation dynamics, whereas it uses Probit regressions to empirically validate the theoretical propositions.

The theoretical conditions show that the stability of farmers' mutual investment in farm-level mitigation measures depends on the relative costs and benefits associated with the investment. The interaction between relative costs and benefits also influences the stability of farmers' cooperation over the exchange of information and resources underlying farm-level adaptation. Farmers' cooperation over sharing adaptation-based information and resources is stable only when non-cooperation incurs a sufficiently higher punishment cost so that the total cost of non-cooperation exceeds that of cooperation. The empirical analysis generates findings that are in accordance with the above theoretically derived conditions. The empirical analysis further finds the significance of farmers' access to extension services, per capita household income and perceptions of climate change in encouraging cooperation when farmers' perceive the cost of non-compliance on others.

That the stability of farmers' cooperation over investing in farm-level mitigation measures depends on the relative strengths of costs and benefits associated with the adoption of the measures. Similarly, the stability of farmers' cooperation over combining mitigation with adaptation measures depends on the additional cost incurred due to the integration of two measures relative to the benefits obtained in terms of a larger reduction in climatic damages. In contrast, the farmers' cooperation over sharing information and resources related to farm-level adaptation is stable when non-cooperation incurs a sufficiently higher punishment cost so that the total cost of non-cooperation exceeds the cost associated with cooperation. The empirical analysis gathers evidence in support of the theoretical findings. The empirical analysis also shows that farmers' cooperation in sharing information and resources related to adaptation measures is significantly influenced by their access to extension services, per capita household income, perception of climate change and future crop loss.

Cooperation among farmers is central to the effectiveness of widespread mitigation and adaptation to climate change in developing nations, especially given the inhibitory role of resource constraints associated with a larger proportion of small and marginal farmers. Addressing the gap in existing literature in terms of not incorporating the dynamic analysis of farmers' cooperation, this study offers a comprehensive investigation of farmers' cooperation over mitigation and adaptation, integrating both theoretical and empirical investigation. The findings of this study are assumed to offer a concrete framework for formulating and implementing suitable policies to foster cooperation among farmers in the study region so that large-scale mitigation and adaptation can be promoted and the region's higher vulnerability and lower resilience can be addressed. The findings are also assumed to apply well to other developing regions characterised to have been experiencing chronic vagaries of climate change and help in policy-making. Finally, the findings of this study offer deeper insights into the role of farmers' cooperation regarding the adoption of different risk-management strategies.

Although this study empirically analyses the effects of reputation loss, its measurement was purely based on farmers' perceptions. Therefore, direct and indirect effects of punishment can be further exploited by designing and implementing more formal penalty mechanisms. The effectiveness of such penalty mechanisms depends on a good institutional framework and efficient regulatory authority, which are often ironically absent in developing nations (Sun et al., 2023b). Furthermore, regulatory authorities in developing nations are often characterised as corrupt institutions, mainly due to substantial regulatory burdens, largely influenced by the large population pressure (Amin and Soh, 2021). The larger population of the state and the study area (Panda and Parashari, 2024) are likely to escalate the regulatory burden. Therefore, the performance of regulatory authorities should be assessed periodically. In addition, the institutional framework should be re-shaped, aligning with principles of integrity, compliance and mutual advantages (Gong et al., 2023) and highlighting the scope and advantages of mutual sharing of risk and returns.

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