## Locus of Control and Economic Decision-Making: A Field Experiment in Odisha, India.\*

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#### Abstract

Farmers who make up the majority of the poor in developing countries are both slow to adopt new technologies and vulnerable to climate change. To become climate resilient farmers must adapt their behaviour. In this paper we investigate potential psychological impediments that make it difficult for farmers to change their behaviour. In particular, this paper evaluates the impact of a randomised multi-pronged psychological intervention that is designed to target locus of control-an individual's belief in their own ability to influence their outcomes – and studies it's impact on the adoption of climate resilient technologies. In the control farmers receive a standard agricultural education about the technologies. Farmers are assigned to one of three treatments where they receive agricultural training and either: a psychological information treatment providing tools to change belief about one's sense of control, a crop simulation app - allowing farmers to simulate their agricultural decisions and a treatment with both combined. Our sample consists of 1674 farmers from 252 villages in Odisha, India. We find that at baseline, the majority of farmers do not believe they can influence their own agricultural outcomes or improve their standing by changing their behaviour. However, with the exception of the crop simulation app, which increases take up of crop insurance, we find little evidence that the information treatment or both change agricultural behaviour, locus of control or aspirations.

## **Key Words:** Psychological Impediments; Locus of Control; Agriculture **JEL Codes:** D01, D91, O13

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### 1 Introduction

A majority of the world's poor reside in rural areas and depend directly on agriculture (Castaneda et al., 2016). These rural communities often face poor living conditions, have less access to essential services compared to urban communities and have very low rates of agricultural productivity (FAO, 2019). This is compounded by two common issues: i) Farmers in developing countries are among those who are most exposed to the harmful impacts of climate change as their production is directly affected by extreme weather conditions (Morton, 2007); ii) farmers under invest and are slow to adopt new inputs and technological innovations, ranging from climate resilient seeds to the use of information technology (McIntosh et al., 2013; Gine and Yang, 2007; Banerjee et al., 2006). The cost of under-investment has broad implications- improved agricultural investment has the potential to increase productivity, food availability, employment, reduce malnourishment and reduce the impact of climate change ultimately leading to a reduction in poverty.

Several external constraints have been studied to understand why farmers fail to invest in potentially profitable innovations. It is possible that they are wary of the riskiness of adopting new agricultural methods or tools (Karlan et al., 2014); they may lack the capital necessary to purchase inputs (Cole et al., 2013), lack information (Ashraf et al., 2009); or they may suffer from high transaction costs reducing the net benefit of adoption (Suri, 2011). Although this set of research has certainly helped to improve knowledge surrounding low take up, there is still significant "unexplained" heterogeneity in technology adoption decisions among rural households (Suri, 2011; Sheahan and Barrett, 2014; Abay et al., 2017) suggesting that external constraints alone are an insufficient explanation. More recently, researchers have turned to internal constraints including stress, depression, patience and biased beliefs as an alternative explanation to understand agricultural behaviour (Banerjee and Mullainathan, 2010; Duflo et al., 2011; Mullainathan and Shafir, 2013; Haushofer and Fehr, 2014; Bernheim et al., 2015; Kremer et al., 2019). This research shows that addressing internal constraints or simultaneously addressing both internal and external constraints could have significant success on a broad spectrum of outcomes (e.g., (Duflo et al., 2011; Banerjee et al., 2015)). However, causal research in this area is uncommon, only a small set of studies conduct randomised trials that are designed to specifically target internal constraints in the context of agriculture (Duflo et al., 2011; Tanguy et al., 2014). This is despite the growing evidence of the effectiveness of interventions targeting these constraints in the domains of health, crime and employment (Ghosal et al., 2020; Blattman et al., 2017; Baranov et al., 2020a; McKelway, 2020; Baranov et al., 2020b; Ashraf, 2021; ?).<sup>1</sup> In

<sup>&</sup>lt;sup>1</sup>For example, Blattman et al. (2017) and Baranov et al. (2020a) conduct psychological interventions using cognitive behavioural therapy targeting criminal behaviour and depression respectively. Ghosal

this paper, we add to this new literature by studying the relationship between Locus of Control (LOC)–an individuals belief in their ability to influence their own outcomes– and willingness to adopt two climate smart agriculture technologies; agricultural crop insurance and stress resistant seeds (STRVs).<sup>2</sup>

We focus on LOC as there is very little research studying the relationship between LOC and decision making in developing countries. More importantly, there are no existing studies that conduct a randomised intervention designed to vary an individuals sense of control in a developing country. This is despite the significant literature suggesting that LOC is a fundamental belief.<sup>34</sup> Previous studies show that: individuals with an internal locus of control are associated with higher investment decisions, including human capital investments (Coleman and DeLeire, 2003; Heckman et al., 2006); higher earnings and labor market outcomes (Goldsmith et al., 1997; Heineck and Anger, 2010) including willingness to participate in training (Caliendo et al., 2020); higher savings and wealth accumulation (Cobb-Clark, 2015; Abay et al., 2017) and more health related investments (Chiteji, 2010; Cobb-Clark et al., 2014). Recent research has also shown that internal locus of control may serve as psychological insurance against negative shocks (Buddelmeyer and Powdthavee, 2016).<sup>5</sup>

An individuals sense of control may be important in developing countries, where people are generally poorer and suffer from larger and more frequent shocks.<sup>6</sup> LOC may be particularly important to understand the low take up rate of products and services in developing countries (often called the last mile problem). For instance, an individual with an external locus of control – who believes that they cannot influence their own agricultural outcomes – may be less likely to invest in new agricultural inputs and are less likely to trust their own abilities or to push themselves through difficult situations.

et al. (2020) studies the impact of an intervention that aims to mitigate psychological constraints on investment behavior of sex workers in India. Ashraf (2021) and John and Orkin (2021) study the impact of visualisation of alternative possibilities on health and entrepreneurship. Recently McKelway (2020) conduct a psycho social intervention to raise the general self efficacy of women in order to increase rates of female employment. Finally, Baranov et al. (2020b) study the impact of a positive psychology intervention on well-being and economic outcomes. None of these interventions target locus of control or the technology adoption of farmers.

 $<sup>^2 \</sup>mathrm{Seeds}$  that have a lower chance of failure during droughts or floods

 $<sup>^{3}</sup>$ We follow Becker et al. (2012) among others and consider LOC as a belief

<sup>&</sup>lt;sup>4</sup>In a related stream of literature, psychologists have argued that locus of control, together with selfesteem, self-efficacy (the belief that one can act effectively to achieve desired results), and aspects of emotional stability, are indicators of a common construct, called "core self-evaluation" (Judge et al., 1998, 2002). A positive core-self evaluation indicates that an individual has a positive self perception of themselves and their ability to influence their own outcomes.

<sup>&</sup>lt;sup>5</sup>Further research in the area of learning has shown that a people with a high internal locus of control, accommodate better and faster to new learning demands, are more intrinsically motivated when it comes to learning (e.g., Bar-Tal and bar zohar (1977); Lefcourt (2014); Rotter et al. (1972) and are more persistent when solving complex problems (e.g. (Wang et al., 2010))

<sup>&</sup>lt;sup>6</sup>In the context of a developed country, research suggests that children who grow up in a household that is financially insecure or suffer other socioeconomic challenges are more likely to develop an external locus of control (Bodovski, 2014; Culpin et al., 2015))

This is relevant as many interventions in developing countries assume that farmers believe they can influence their own outcomes (i.e., they have an internal LOC) and are *willing* to change their behaviour, all that is missing is knowledge, capital or access to the product. If LOC is important then these standard solutions may be ineffective.

The experiment which is pre-registered is conducted using a unique state representative sample of 1674 farmers from the Indian state of Odisha.<sup>7</sup> Using the general locus of control measure we find that prior to the intervention, over 64% of all farmers in our sample believe they have little control over what happens, and 76% believe luck is very important in their lives. We also use a agriculture specific locus of control measure which shows that prior to the intervention 68% report they have little control over their agricultural outcomes, and 72% believe their agricultural production does not depend on the effort they put in. These findings suggest the majority of farmers have an external locus of control. We also show that external LOC is correlated with a lower probability to take up insurance and crop insurance. This is consistent with Abay et al. (2017) which is the only other research that studies the correlation between locus of control and farmers' technology adoption in a developing country. They show strong evidence that external LOC is negatively correlated with use of chemical fertilizers, improved seeds, and irrigation practices in Ethiopia.<sup>8</sup>

A novel feature of this study is that we also conduct a randomised control trail targeting the LOC of these farmers. All farmers in our sample received agricultural education that aimed to inform them about crop insurance and STRVs including how and where they can be bought and their benefits and costs. In the control farmers only received this agricultural training. The experiment contained three psychological treatments that were specifically designed – and based on theoretical foundations – to target LOC. First, a randomised subset of farmers participate (in addition to the agricultural information) in an information and education session aimed at increasing their belief about their ability to control their agricultural outcomes. This includes discussions about how they and their peers have overcome agricultural issues, how to set and achieve goals, discussion by role models about overcoming adversity and discussion about the influence of negative beliefs on behaviour. Second, a randomised subset of farmers played a farming simulation game given after the agricultural training. They are faced with all the decisions a farmer may make such as what methods and inputs to use and whether to register for insurance. Similar to real life they could also experience weather shocks (based on the real expected probability in the area). Farmers play the

 $<sup>^7\</sup>mathrm{The}$  pre-analysis plan can be found on the AEA Social Science RCT Registry ID Number AEARCTR-0005645

<sup>&</sup>lt;sup>8</sup>This paper also differs from the excellent Abay et al. (2017), who measure LOC using a general LOC instrument, in this paper we use a specific agricultural LOC. This may be important as, it has been shown that locus of control can be context specific, that is whether they are external or internal may vary based on the context (Galvin et al., 2018; Johnson et al., 2016)

game for 5 seasons. At the end of every season, they directly observe counterfactuals such as what would have happened with/without agricultural insurance. This intervention was implemented as psychologists believe that one way to change beliefs about control is for people to experience or imagine how their decisions impact their outcomes (Pajares et al., 2007; Bautista, 2011; Usher and Pajares, 2006a; Ashraf, 2021; John and Orkin, 2021). The final intervention combines both the information based psychological intervention and the crop simulation app.

The control and treatments were either delivered by a more traditional classroom approach or in the format of an edutainment video. Differences in the mode of transmission allows us to contribute towards the growing literature showing that transmitting information in an entertaining format is an alternative method to improve information take up (Vogt et al., 2016; Banerjee et al., 2019; Green et al., 2020). While this literature has shown that edutainment is effective in reducing domestic violence (Banerjee et al., 2019; Green et al., 2020) and changing gender attitudes (Vogt et al., 2016), these different modes have not been studied in the context of a direct psychological intervention. Further, there is limited research directly comparing edutainment to a standard more common classroom information transmission. We therefore, add to this literature by directly comparing classroom to edutainment as a mode of information transmission in a developing country context.

We find robust evidence that the interventions, irrespective of mode of transmission have *no* positive influence on an individuals sense of control. Regarding agricultural outcomes, with the exception of the crop simulation app (alone), which increases crop insurance by 13.5 pp (over a 100% increase), neither the information based psychological intervention or both joint have an impact on agricultural decision making including take up of insurance or STRVs, use of agricultural inputs or aspirations. The impact of the crop simulation app on crop insurance is robust to multiple hypothesis testing. We then conduct multiple robustness tests of the mostly null results.<sup>9</sup> We test for heterogeneity using a double lasso method to select controls and test whether our results are due to a lack of power to detect effects. Similar to our main results, with the exception of the crop simulation app, which only has a robust positive impact on crop insurance, these robustness tests allow us to conclude that our psychological locus of control interventions have little positive impact on agricultural outcomes. Finally, although not pre-registered, we study explanations for our results and rule out the ineffectiveness of the pure agricultural information treatment, the role of Covid-19 which enforced lock downs half way through our endline data collection and subject fatigue.

We speculate that our results are due to the light touch nature of our interventions. Our findings raises doubts that small scale psychological interventions, that rely on

<sup>&</sup>lt;sup>9</sup>These tests were not pre-registered.

one off information sessions, are an easy and affordable way to improve take up of agricultural products or change decision-making in developing countries. However, our results also suggest that mobile technologies such as specifically designed apps which can be used to provide information in a more entertaining fashion have potential to influence agricultural behaviour.

## 2 Design

The experiment is specifically designed to target individuals' self evaluation and in particular their belief in their ability to influence their outcomes in the agricultural sphere. In what follows we will refer to locus of control as simply control.

### 2.1 Agricultural Insurance and STRVs

This paper focuses on the take up of agricultural insurance and STRVs. We focus on these two products as there is significant existing evidence that they mitigate climate risk and also improve agricultural outcomes. We explain this further below.

#### Agricultural Insurance

Agricultural insurance that pays out in times of agricultural loss due to weather shocks are expected to smooth income and reduce the impact of climate change. There are now several studies that examine the impact of agricultural insurance. These include Mobarak and Rosenzweig (2013) in India, Cai et al. (2015) in China and Karlan et al. (2014) in Ghana. The first two studies find evidence that insurance causes a switch towards crops that are more profitable but riskier. The latter two find evidence that insurance leads to higher investment and yield. Overall, this suggests that taking up agricultural insurance can be welfare improving.

In this paper we use the national government's Pradhan Mantri Fasal Bima Yojana (PMFBY) index based (yield) crop insurance program as the reference insurance product. This is the main agricultural insurance product in India. The scheme covers a set of covariate production risks such as yield losses due to natural calamities, prevented sowing and post-harvest losses (GOI 2018). Despite subsidies of up to 88% by the state government, only 9% of eligible farmers had registered for agricultural insurance in Odisha at the time of our baseline survey. These subsidies ensure that buying the insurance in our setting is actuarially fair, meaning the premium costs is on average equal (or less than) the expected benefits. It is plausible that an individual who has an external control actually believes that they cannot influence their outcomes– because they are determined by the weather. Such a person may be more inclined to buy weather insurance. Alternatively, an individual with an external locus of control who believes that their effort or changing their behaviour will not change their outcomes may be inclined to avoid buying agricultural insurance. We expect the latter is more common, as we found a strong negative correlation between external locus of control and take up of agricultural insurance at baseline. Further, this latter result is similar to that found in Abay et al. (2017).

#### STRVs

A second solution to mitigate adverse weather events is to adopt climate smart practices that have lower probability of crop failure under adverse weather conditions. New stress resistant crop varieties such as those studied in this paper increase yield by as much as 30% in the event of adverse weather conditions. Emerick et al. (2016) studies a similar STRV by randomising access to flood tolerant rice varieties in India. The authors find that farmers given STRVs change their agricultural practices and the type of seed used, increasing yield. The authors also show that STRV farmers cultivate more land and spend around 10 percent more on fertilizer the year after STRV use. This suggests that STRVs can increase yield during periods of adverse weather conditions as well as normal conditions (Emerick et al., 2016). In this project we use a similar type of STRV as studied by Emerick et al. (2016). Given that the yield of the STRVs are first-order stochastic dominating, we know that any delay in its adoption is a non-optimal decision that could affect wealth accumulation (Emerick et al., 2016).

#### 2.2 Interventions

In this subsection we outline our intervention and discuss the rationale for including each design aspect.

The experiment consisted of a  $2^{*}2^{*}2$  design, see Figure ??. All of the farmers in the sample took part in agricultural training aimed at increasing farmers' take up and awareness of crop insurance and stress tolerant rice varieties. There were two main modes by which the agricultural intervention was transmitted, these were; via traditional classroom training and edutainment video training. Approximately half of the farmers were also randomly assigned to the psychological control **information** intervention, directly aimed at increasing an individuals sense of control. Further, as psychologists have hypothesised that belief about one's control may be influenced by imagining ourselves or others behaving efficiently in hypothetical situations the experiment also tests if a crop simulation farming game can impact farmers' behaviour (Williams, 1995). This treatment is randomly assigned to about half of the sample. The farmers who were only given agricultural training, constitutes the control condition (473 observations) while the farmers who were given agricultural training in combination with the information based psychological control intervention constitutes the first treatment (464 observations). The second treatment are those assigned to play the crop simulation app (377 observations) but who did not receive the psychological information and the final third

treatment are those who took part in both the psychological information treatment and the crop simulation app (437 observations).

Information	Psychology	Арр
	Locus of control	
Edutainment	No Locus of contro	No Simulation App

The purpose of this paper is to study if the farmers who were given the psychological control information intervention, the crop simulation app or both differ in terms of their sense of control, economic decision-making and aspirations compared to the farmers who were not assigned one of these treatments. Finally, as secondary analysis we also examine whether the mode of education (edutainment vs classroom) has a differential impact on outcomes. The pre-analysis plan outlining our design and outcomes can be found in the AEA Social Science RCT Registry ID Number AEARCTR-0005645. Unless otherwise stated, we follow the registered pre analysis plan.

The interventions were organised in the following way; the agricultural training in the form of classroom or edutainment video training was given first. The information based psychological control intervention (if given) was part of the agricultural training. The crop simulation app (if given), occurred directly after the agricultural training session.

Our experimental setup and setting is unique as we include a number of elements to improve experimental control and reduce other common explanations for low take up. In particular, first, both agricultural products are heavily subsidised by the state government, to buy one acre of insurance costs between 324-519 INR<sup>10</sup> (this varies depending on risk in the district) which is between 1.3-2.1 days wage for males in this area. While seeds for 1 acre costs around 400 INR, since most farmers have 2.54 acres, this is equivalent to about 1.6 days wage. This low cost of usage should reduce potential credit constraints as a explanation for low take up. Second, the subsidy of the insurance premium is such that taking up insurance is at least on average actuarially fair,<sup>11</sup> while the STRVs are genetically identical to the existing variety used by nearly all farmers (and cost almost the same) except they have a higher resistance to droughts and floods.<sup>12</sup> This suggests that there are clear benefits from taking up the products, reducing concerns about the influence of risk, a common confound. Third, to reduce farmer transaction

 $<sup>^{10}</sup>$ Indian Rupees

<sup>&</sup>lt;sup>11</sup>The premium is at least equal, on average, to the expected probability of a claim multiplied by the amount paid out in the event of a claim.

 $<sup>^{12}\</sup>mathrm{This}$  means the STRV seeds do not use different methods or inputs from what the farmers are used to.

costs, STRVs were made available through government common service centers (CSC), located in each grampanchayat where the experiment is implemented (the seeds were also available from private vendors). Further, administrators of the CSC were trained on how to help farmers apply for agricultural insurance and supply STRV seeds using vouchers. Farmers who were not able to use the online agricultural insurance sign up forms, could also register for insurance at these service centers. Fourth, all farmers in our sample are educated about the two products, reducing concerns about a lack of information, another common explanation for low take up. The effect of the pure education intervention (without any psychological components) is discussed further in Section 4.5.

#### 2.3 Agricultural Training

#### 2.4 Classroom

Those farmers assigned to the classroom mode of education took part in a classroom training on weather related risk, crop insurance and STRVs. The trainer first informed the farmers about the government-initiated crop insurance program, PMFBY. Here the farmers learned about the coverage of the program, eligibility, registration and the premium amount. The trainer further explained how the government evaluates crop loss, the risks faced by the farmers and the terms for compensation. The farmers also learnt about STRVs and how the use of these may mitigate weather-related risks. Finally, they learnt how to obtain both of these products. This type of education is very similar to agricultural extension programs implemented world-wide on related agricultural topics.

#### 2.5 Edutainment

Recent research such as Banerjee et al. (2019) and Green et al. (2020) show that providing information in the form of entertainment can be an effective strategy to distribute information. The core argument is that people may learn about new behaviours by observing others in fictional dramatizations (Bandura, 2004; Green et al., 2020). In our edutainment intervention, the farmers watched a fictional and informative film on weather related risk, crop insurance and stress tolerant rice varieties. To increase the probability that the farmer absorbs the information, the film was made entertaining and in Odiya, the local language. The information given in the film corresponded for the most part to the information conveyed to the farmers in the classroom training. To make the film relatable, it took place in a rural setting in Odisha in which the main characters were two farmers. In the film, one of the farmers had just encountered crop failure due to weather related factors and reaches out to his fellow farmer for help. His friend, unlike himself, had registered for crop insurance prior to the agricultural season and suggests this as a future solution to crop loss. The two farmers were then met by an educator who answered their questions regarding crop insurance, stress tolerant rice varieties and weather risk. The film shifted from a fictional setting to an informative lecture when the educator conveyed the information to make it easily accessible for the farmers.

### 2.6 Psychological Control Interventions

Since our aim is to test whether changing an individuals belief in their ability to influence their outcomes impacts the take up of our two agricultural products, we conduct multiple treatments designed to target an individuals belief in their ability to control their outcomes.

According to early psychological research such as Lefcourt (1982), the concept of LOC can be subdivided, into fixed and variable rates of stability. For example, a person may consider an outcome to be the result of ability which is fixed and effort which is variable. This concept is relevant in our context as the aim of our interventions are not to effect the fixed state i.e., the probability of being impacted by a negative climate shock, but rather the variable state, that is the effort one can put in to overcome such a shock.

In what follows we outline the details of the psychological control interventions and the rationale for each treatment.

#### 2.6.1 Psychological Control Information Intervention

The goal of this treatment was not to evaluate any one particular LOC intervention, but rather to create a comprehensive intervention that contained multiple parts with the aim of moving LOC and ultimately agricultural behaviour. To this end, based on a review of the literature studying psychological control (see for example (Bandura, 2010)), this intervention contained multiple elements which have been at least theoretically suggested to impact an individuals sense of control. We discuss each element in turn.

#### **Observing Experience**

**Classroom:** Research suggests that observing the experiences of highly relatable individuals is an important factor in an individuals sense of control (Bandura, 2010; Usher and Pajares, 2006b; Bernard et al., 2014). To include this concept in our intervention, the educator read out multiple examples of real farmers from Odisha who overcame their agricultural problems by active decision-making such as registering for crop insurance or using STRVs. Farmers then discuss in a large group what they thought of this farmers experience. To ensure the examples were relatable, the example farmers were actual farmers from the local area who had suffered common issues prevalent locally.

The educator also asked one or two farmers in the session to share and describe a situation where their actions led to improvements in agricultural outcomes, for example by describing how they made the change. This could be regarding the usage of inputs, methods or other factors relevant to the farmers.

Edutainment: Similar to the classroom training, the edutainment video was designed so that it contained a vicarious experience that would be highly relatable to the subjects. In particular, the film takes place in a rural, village setting in their home state, Odisha. The main characters are two farmers who speak the local Odia language. The agricultural problems they encounter in the film are problems faced by a large share of farmers in the state. Secondly, the edutainment includes a section where real farmers from their state were interviewed regarding their experience. The interviewed farmers talk about how they encountered crop failure and had managed to overcome their difficulties by active decision-making such as registering for crop insurance. The content of the information given to the subjects corresponded to the information conveyed in the classroom training.

#### Social Persuasion

Classroom: Research also suggests that social persuasion can positively influence an individuals sense of control (e.g., Bandura (2010); Usher and Pajares (2006a); Bautista (2011)). The intervention therefore also includes sections specifically focusing on verbally convincing the farmers that they have what it takes to achieve their aspired outcomes. For instance, the educator emphasised and discussed the role of a person's belief in their own ability to achieve given outcomes. The educator described beliefs in ones own ability to achieve outcomes as an important determinants for which goals an individual sets for themselves and further, for the level of effort a person decides to put into achieving these goals. The aim of this information was to make people aware of the potential impacts of their beliefs on behaviour. As discussed by Kremer et al. (2019) the scarce evidence suggests individuals are naive about the impact of psychological impediments on decision making. The educator also explained how farmers may choose not to register for crop insurance because they do not believe in their ability to understand how the insurance works or because they do not believe themselves able to control their own situation. The educator then emphasised how such beliefs are just beliefs and do not define what is truly possible and quoted Mahatma Gandhi; "If I have the belief that I can do it, I shall surely acquire the capacity to do it even if I may not have it at the beginning".

**Edutainment:** Like the classroom session, the film includes sections where the educator attempts to verbally convince the two farmers that they have what it takes to achieve their aspired outcomes. For instance, the educator emphasises the role of a person's beliefs regarding their own ability to achieve given outcomes. As in the

classroom, the educator in the film explains how farmers may choose to not register for crop insurance because they do not believe in their ability to understand how the insurance works or because they do not believe themselves able to influence their own outcomes. She underlines how such beliefs are just beliefs and do not define what is truly possible. Like in the classroom training, the educator proceeds by emphasising how an individual truly has the power to influence their own outcomes and cites Mahatma Gandhi; "If I have the belief that I can do it, I shall surely acquire the capacity to do it even if I may not have it at the beginning".

#### **Goal Setting**

**Classroom:** Recent research suggests that motivation, performance and in turn a sense of control can be positively influenced through goal setting (Bandura, 2010; Erez and Judge, 2001; Schunk, 1990; Schunk and Swartz, 1993; Hsiaw, 2013; Locke and Latham, 2002). To achieve this, the classroom training included a section where the subjects were told to set agricultural goals for themselves. The educator underlined how belief in ones ability to influence outcomes is not a fixed state of mind but a belief that could be changed through simple mental exercises. The subjects were asked to write down 2-3 goals related to their agricultural activities and for each goal they were expected to list what they can do to achieve it. These were discussed in groups of three together with the educator who helped the subjects think of and write down the smaller steps required to achieve their goals. The subjects were encouraged to continue with goal setting on their own and to continuously reflect on the goals they have set for themselves and on the process needed to fulfil them.

**Edutainment:** The edutainment mode did not include an actual goal setting exercise as no physical trainer was in the room to supervise the farmers. However, the film includes a goal setting discussion where the educator suggests that one way to achieve desired outcomes is to set clear goals and follow them regardless of obstacles and challenges. The educator further suggests that any action is easier to understand and undertake if each task is broken into steps which may then be systematically followed and encourages the farmers to apply this method to their own tasks.

#### 2.6.2 Crop Simulation App

**Hypothetical Experience** Another potential way to influence a sense of control is by experiencing success (Usher and Pajares, 2006a), or imagining ourselves or others in hypothetical scenarios (Williams, 1995). A potential means to do this is through video games which as discussed in a review of the literature have also been shown to positively influence health related behaviour (Thompson et al., 2010).

To target this we created a farming simulation game - **crop simulation app**. The app illustrated a hypothetical scenario in which the farmers applied the new information they acquired in the agricultural training and in which they could observe the consequences of their decision-making directly. The farmers made choices regarding inputs (like fertiliser and STRVs), agricultural methods, crop insurance and expenditure on their children's education (household budget allocation). Depending on their decisions, the subjects faced different risks of crop failure, which in turn resulted in different scenarios of yield and profit. The farmers could for instance encounter scenarios of drought or flood (similar to real life scenario), from which they were more or less financially affected depending on whether they decided to register for crop insurance and on their usage of STRVs. To make these scenarios realistic, the probability of encountering them were based on data from each farmers' local district (e.g. occurrence of flood and drought) and options (e.g., on what inputs to use) were based on common usage/practices in the local area. The whole season including decisions were animated.

The educator began by introducing the game to the group after which the subjects individually played five rounds with an enumerator to make sure that the farmers understood each decision and how to use the app. At the end of each round, farmers were shown the counterfactual (what would have happened if they did/did not take up the products). As the farmers played the game over several rounds, they were given the chance to revise or sustain their decision-making based on the experience and learning from their performance (e.g. yield and profit) in previous rounds. The app was thus, a method to simulate the results of their changed or unchanged behaviour and enable us to understand decision making under uncertainty.



**Figure 1:** Sequences from the crop simulation app Notes: These are screenshots taken from the English version of the crop simulation app.

## 2.7 Combined Information Intervention and crop simulation app

The final treatment involves both the information based psychological control treatment and the crop simulation app treatment. This allows us to estimate the benefits of both treatments and assess whether there is a greater impact from combining them.

## 3 Data and Sample

A baseline survey was implemented in April 2018, followed by the experiment in May 2019 (prior to the start of the agricultural season) and an end-line survey commencing January 2020 (at the end of the same agricultural season). Close to half of the endline data was collected before the outbreak of Covid-19 and the subsequent lock down of India, the residual was collected in person in January-February, 2021.<sup>13</sup> We discuss potential issues as a result of Covid-19 and recall bias in Section 5.2.

The data collection took place in the state of Odisha, India, where over 60 percent of the workforce depend on agriculture, 90 percent of the farmers are small and marginal, with an average land holding of 1.25 ha (Odisha, 2017). The main cultivated crop is rice, covering about 90 percent of the agricultural land. The average rice productivity is below the national average (Odisha, 2015). A varying climate implies that some areas face a risk of drought while other areas flooding. The Indian cropping seasons are divided in to Kharif (June - October) and Rabi (November-April) based on the course of the monsoon (Odisha, 2015).

To implement the experiment, we first randomly selected 15 out of Odisha's 30 districts to participate in the study. From each of these 15 districts, using the probability proportional to size sampling approach, 300 villages were randomly selected (using the 2011 Indian census 2011). From the selected villages, we conducted a village census of all farming households. From these village census of over 70,000 households, we randomly selected 10 households in each village resulting in a sample of 3000 households. As discussed in the pre analysis plan, in this project we exclude 48 villages as they are pure control (without any intervention) and from each village we only used 8 observations (2 were spill over control i.e., they recieved no intervention at all). This leaves us with a sample of 2016 households. We discuss the impact of the agricultural only intervention (the pure control) in Yashodha et al. (2021) and in this paper in Section 5.1. Our endline sample of this size. Of those in our endline sample only 4% were unavailable to attend the interventions, giving us a very high complier rate. As such we consider our treatment

<sup>&</sup>lt;sup>13</sup>This was before the onset of the second wave. Use of an in-person survey was approved by the local government and conducted by enumerators who resided in the local area

estimates as average treatment effects.<sup>14</sup> Our sample size is over 10 times larger than the average sample size in the psychology literature for positive psychological interventions such as self affirmation interventions where the average starting sample size is about 150 individuals (see Baranov et al. (2020b), for a detailed discussion about sample size in the positive psychology literature). We discuss our minimum detectable effect size calculations in Section 4.5.

On the day of the experiment, a private car collected each farmer within the village and brought them to a central location within the same sub-district. All training sessions were conducted in a government community center. There was one session conducted each day and each session contained subjects from 4 villages. This means there was only one session per village. Within each session we simultaneously ran the edutainment and classroom interventions (in separate rooms). Half of the sample within a village were assigned edutainment with the residual assigned the classroom intervention. The crop simulation App treatment was assigned at the village level and all subjects under this treatment within the training session received the hypothetical experience using the simulation app. An educator explained the crop simulation app to the groups in both the classroom and edutainment treatments. Thereafter, with the support of an enumerators each individual farmer played the game. The psychological information intervention was assigned at the session level, meaning within a session all villages received the psychological control information or they did not.

We report the balance table comparing important demographics between the control (without any psychological intervention) and the pooled psychological interventions in Table 1. As expected we find very little difference across treatments.

#### 3.1 Key Variables

We elicited two measures of Locus of Control. Following common practice we estimate a 6 item general locus of control. The farmers were asked to rate the accuracy of the following statements; 1) "I have little control over what happens to me" 2) "Every time I try to get ahead, something or somebody stops me" 3) 'It's not always wise for me to save because many things turn out to be a matter of good or bad fortune" 4) 'Luck is very important for what happens in my life" 5) "I find it hard to save money for the future" and 6) 'I have not achieved what I deserve".<sup>15</sup> For each question respondents are asked to provide their response on a five-level Likert-scale of agreement/disagreement. A higher number indicates respondents are more likely to **disagree** with the statement. As such disagreeing indicates internal control and agreeing as external control for question

<sup>&</sup>lt;sup>14</sup>All our results are highly robust to estimating a Local Average Treatment Effect (LATE) model i.e, excluding the non compilers

<sup>&</sup>lt;sup>15</sup>Some of the items were slightly modified from the standard version to improve understanding within our context.

1-4 and 6 and the reverse for question 5.

As multiple studies have shown that LOC can be context dependent - we administered our own separate 3- item agricultural specific locus of control (Johnson et al., 2016; Galvin et al., 2018). Both at the baseline and endline farmers were asked to rate the accuracy of each of the following statements; 1) "Luck is very important for what happens to my agricultural production." 2) "I have little control over what happens to my agricultural production." and 3) "My agricultural production does not depend on the amount of effort I put in". A higher number indicates respondents are more likely to **disagree** with the statement.<sup>16</sup> It is important to note that the general locus of control was not collected at baseline. At baseline, we were simply conducting exploratory work to understand the importance of different internal constraints (prior to the design of the intervention). As such we focus on the agricultural LOC when using baseline data.

Following the pre-analysis plan, for each LOC measure the variables were standardized and summed into indexes with equal weights. In addition to this, we also follow Cobb-Clark (2015); Piatek and Pinger (2016); Awaworyi-Churchill et al. (2020) and employ factor analysis to re weight the survey items. This is discussed further in Section 4.3.

In this paper, we are interested in the influence of our intervention on changes in agricultural behaviour. As the interventions focus on improving take up of insurance and STRVs we focus on these as our main dependent variables. The first outcome variable is the binary variable "Insurance", taking the value 1 if the respondent registered for any insurance including agricultural, health and home and 0 otherwise. The more specific second variable "Crop Insurance" is a binary variable taking the value 1 if the respondent registered for crop insurance and 0 otherwise. The third variable "Fertilizer" is a continuous variable corresponding to the amount of fertilizer used per 100 kg of paddy grain produced. We use this variable as it is a useful measure of a key input into production. Changes in this variable may suggest a change in effort. As a further measure of the change in agricultural practices we define a variable called "Agricultural Practices". For each agricultural practice we ask if they have increased, decreased or left the input unchanged. In our survey, there are 18 possible agricultural practices (e.g., use of pesticides, herbicides, irrigation, weeding ect) which the farmers may or may not have chosen to increase since the last growing season. Each time an individual increases usage the value of this variable increases by one unit. If this variable takes the value 0, the respondent decreased or did not change all the inputs or labour usage. In contrast, if this variable takes the value 18, the respondent chose to increase all practices. This is a measure of effort put into the agricultural process post training. The variable STRV

<sup>&</sup>lt;sup>16</sup>Both measures focus explicitly on measuring external locus of control. We assume an individual with a low external control has high internal control.

is equal to one if the farmer used a STRV.<sup>17</sup> Finally, we measure a farmers aspired agricultural yield. In particular, in the survey the farmer is asked the amount of rice yield in quintals per acre they aspire to have in five years' time. This outcome variable should be interpreted with caution. Unfortunately around 50% of our sample had issues with this question—many did not have aspirations or found it difficult to understand the term. As a result there are a large number of missing observations. Despite this issue, for full transparency and to ensure consistency with our pre analysis plan we do not exclude this variable.<sup>18</sup>

## 4 Results

#### 4.1 Descriptive Statistics

Descriptive statistics are presented in Table 2. The descriptive statistics for the baseline data show that approximately 25% of the individuals in our sample were registered for some type of insurance prior to the intervention but only 9% were registered for crop insurance. The average age in the sample is approximately 51 years. As this study specifically targeted those responsible for farming, the share of women in the sample is only 7% percent. Average annual income is approximately 131 000 INR (1700 USD). The mean years of education is approximately 6 years. While general caste constitutes 7% of the sample, 14% of them belonged to "Scheduled Castes" (SC) and 23% as "Scheduled Tribes" (ST). As many as 47% percent of the individuals are from "Other Backward Classes" (OBC) and further, 9% percent belong to "Socially and Economically Backward Classes" (SEBC). Lastly, around 99% of the individuals in the sample identify as "Hindu".

The LOC related variables in Table 3, the baseline measure shows that 64% of farmers agree or agree strongly that they have little control over what happens to them and 59% believe that when they try and get ahead something/somewhat stops them. While 76% believe that luck is very important in what happens to them and 48% believe they have achieved what they deserve. Turning to the agricultural specific measures, around 68% agree or agree strongly that they have little control over their agricultural production and 79% believe that luck is important for their agricultural production, finally, 72% believe that their production does not depend on the amount of effort they put in. This suggests that many individuals have an external locus in general and also in relation to agricultural production.

The summary statistics for the endline data suggests that 43.7% of the sampled

<sup>&</sup>lt;sup>17</sup>This variable was inadvertently omitted from the pre analysis plan but as a direct measure of one of our agricultural products we believe it is important to include.

<sup>&</sup>lt;sup>18</sup>As a robustness test we create a variable equal to one if they answered the aspiration question and zero if it was skipped. Our main are similar in sign and statistical significance.

individuals were registered for some type of insurance (compared to 25% at baseline p=0.000) and 21.5% were registered for crop insurance (compared to 9% at baseline p=0.000. While 32% of farmers were using STRVs. The average number of increased agricultural practices since teh last season is 0.519. Aspirations defined by the respondents' aspired agricultural yield in five years' time is only measured at endline and has a mean of 20.513 quintals per acre.

## 4.2 Is Psychological Control Correlated with Decision Making?

While locus of control has been shown to be correlated with farmer behaviour in rich countries, with the exception of Abay et al. (2017) this connection has yet to be robustly tested in low income countries. As a first step to understand the relationship between LOC and farmer decision making, we estimate the following OLS model

$$y_i = \alpha + \beta ALOC_i + \delta X_i + \gamma V_i + \eta_i \tag{1}$$

The dependent variable  $y_i$  corresponds to the four outcome variables measured at baseline and described in Section 3.1; Any Insurance, Crop Insurance, Changed Variety and Fertilizer. The independent variable ALOC index corresponds to the agricultural control index. At baseline we only measured ALOC and not GLOC. X corresponds to a vector of socioeconomic and demographic control variables (Age, Income, Gender, Caste and Educational level) and V corresponds to village fixed effects. Standard errors will be clustered at the village level.

The results from the regressions (Equation (1)) testing the relationship between control and economic decision-making at baseline are presented in Table 4. The results in Column 1 suggest that a one standard deviation increase in psychological control (a greater probability of being an internal LOC) is associated with a 5.5 percentage point increase in the probability of registering for any insurance and a 1.9 percentage point increase in the take up of crop insurance. These results are statistically significant at the 1 and 10 percent level respectively and are robust to the inclusion of socioeconomic and demographic control variables. However, for both changed variety and fertiliser, we find little correlation between our measure of control and the other agricultural outcomes.

It is important to stress that this is only a correlation, a statistically insignificant relationship does not imply that changes in LOC will not impact agricultural decision making. First, the number of individuals that use insurance and improved seed varieties is very low, reducing potential variation. For instance, at baseline only 9% of our sample use agricultural insurance.Second, without knowledge and information about our agricultural products, there is no process by which someone even with internal control can take up these products. Based on our baseline data 70% of subjects had not heard of the PMFBY agricultural insurance program. Similarly, 55% of farmers had no knowledge of STRVs.<sup>19</sup> Our RCT accounts for this by educating our whole sample about both products. Third, at least theoretically, an individual who believes they cannot influence their own agricultural outcomes should be less likely to change their practices. Therefore, what is important is not only the baseline correlation but the influence of a change in LOC on our outcomes. Again our RCT aims to change LOC and can therefore help to answer this question.

#### 4.3 Does the Interventions Impact Agricultural Outcomes?

To test the impact of our psychological interventions on psychological control and economic decision-making the average treatment effect will be estimated with the following model:

$$y_i = \alpha + \delta A l l P C I_i + \eta_i \tag{2}$$

where  $AllPCI_i$  corresponds to one if farmers participated in any of the psychological control interventions i.e., either the psychological control information intervention, the simulation app or both of them jointly. The pooled psychological treatment effect should be interpreted as conditional on the distribution of the other treatment (Muralidharan et al., 2019). We start by pooling the edutainment and classroom mode of transmission. Standard errors are clustered at the session level as this was the randomisation unit of the psychological control information treatment.

Table 5 presents the treatment coefficient of the psychological control intervention on an individuals sense of control and economic decision-making. We also report the treatment effects from these models in Figure 2. We find little evidence that the pooled psychological intervention impacts either general locus of control or the agricultural locus of control. As shown in Figure 2 point estimates are close to zero and confidence bands are small, suggesting a null relationship. Turning to our agricultural variables, we find a positive and very marginally statistically significant impact on insurance (p=0.095) and in the same direction but less statistically significant crop insurance (p=0.145), however, again there is little change in our other variables like STRVs, fertiliser use or changes in agricultural practices. We find similar result when we split the sample by mode of transmission, reported in Table A1, Panel A and B. In our edutainment setting– the treatment has a positive impact on crop insurance and any insurance at the 10% level of significance. However, in the standard classroom training, there are no statistically relevant relationship between our outcomes and treatments.

<sup>&</sup>lt;sup>19</sup>Since this was measured at endline only, this number comes from the sample who did not receive any agricultural training

We test the robustness of our LOC index, following other LOC studies in economics (see: Cobb-Clark (2015); Piatek and Pinger (2016); Awaworyi-Churchill et al. (2020) ) by calculating the predicted factor obtained from a principal component analysis instead of assigning equal weights to the individual items in the LOC index. This approach generates a weight for each item in the overall index. The index is standardised to have mean 0 and standard deviation 1. Similarly, the LOC index is increasing in internal control. Key results are shown in Table 6, Panel A. Results are very similar suggesting the null relationship between psychological control and the psychological intervention is robust to a different definition of LOC.

As a further robustness we use both baseline and endline data to estimate a difference in difference model. We do not report the outcome aspirations, and the general locus of control measure, which were both only collected during the endline (which is why our preferred estimation is Equation 4.3). Results are reported in Table A5 and by mode of transmission in Table A7. Our results are very similar– there is very little evidence that the psychological interventions, regardless of training mode, has a **positive** impact on our outcomes. Again, the exception is crop insurance, in the Edutainment setting the pooled psychological control intervention has a 5.3 pp positive impact on crop insurance (p < 0.10).

In summary, these results indicate that the psychological control interventions when pooled have little positive impact on locus of control, economic decision-making and aspirations. The key exception is the impact on the take up of crop insurance, especially in the edutainment setting. We investigate this further in the following subsections.

#### 4.4 Results by Psychological Control Treatments

Equation 4.3 did not separate the impact of the different possible psychological control interventions. To do this, we estimate the following model

$$y_i = \alpha + \delta_1 PCIInfo_i + \delta_1 SimA_i + \delta_2 Both_i + \eta_i \tag{3}$$

where  $PCIInfo_i$  is equal to one for those that only participate psychological control **information** treatment but not the simulation app,  $SimA_i$  corresponds to those who only participate in the Simulation App but not the psychological information treatment and  $Both_i$  is a dichotomous variable, equal to one for those that participate in both. The excluded group are those who do not participate in any psychological control intervention but only the agricultural training. Standard errors are clustered at the session level.

The results are presented in Table 5 and Figure 3, and by training mode in Table A1, panel C and D. There are three key takeaways. First, irrespective of training mode, there are no treatment effects on our measures of control, suggesting the interventions

do not impact farmers belief in their ability to influence their outcomes. Second, in the edutainment training mode, the psychological control information intervention has a positive impact on any insurance at the 5% level of statistical significance. We also find that the simulation app intervention, again in the edutainment treatment has a 11.0pp impact on the take up of crop insurance. Third, other than these changes in insurance, the treatments have little positive impact on aspirations and decision making.

Again, where possible, for robustness we control for the baseline value of the dependent variable, presented in Table A6 by estimating a DID model. We find very similar results. The only training mode to have an impact on outcomes is edutainment, where the psychological information treatment has a positive change on insurance and the simulation app leads to a positive change in the take up of insurance.<sup>20</sup>

While we do find positive impacts for insurance and crop insurance, these are only two outcomes out of many tests. In most cases we find no positive relationship. As a further robustness we adjust for multiple hypothesis tests. Considering that we investigate treatments both pooled and split, which produces three types of psychological interventions (simulation app, information treatment and both) and two modes of training (classroom or edutainment) for eight outcome variables, almost 100 statistical hypotheses are tested in the main analysis. With a selected probability of making a type 1 error of  $\alpha = 0.05$  for an individual test, conducting multiple tests will imply the probability of rejecting a false null hypothesis will increase drastically. The family wise error rate (FWER) is the probability of making one or more false discoveries when performing multiple hypothesis tests and will be equal to  $FWER \leq 1 - 1 - \alpha k$  where k is the number of tests conducted Clarke et al. (2020). If 100 statistical hypotheses are tested, the probability of falsely rejecting at least one true null hypothesis will be  $FWER \leq 1 - (1 - 0.05)^{100} \approx 0.994$  almost certain and since we only have a handful of statistically significant results, this is highly relevant. To account for this in the analysis we use the Romano-Wolf correction. This method, unlike the classical Bonferroni and Holms correction has more power as it uses bootstrap resampling from the original data and takes the dependence structure of the p-values into account when calculating the FWER (Clarke et al., 2020). The adjusted p-values associated with the estimations from equation 4.3 and 3 are reported in Table ??. As expected, the adjusted results suggest that the intervention has no impact on psychological control, it also shows that the psychological information intervention has no robust impact on most of our outcomes. The only intervention that has a positive impact (on crop insurance) is the simulation app, suggesting the previous relationship found between the psychological control information intervention and crop insurance is not robust. It is worth noting that while the simulation app leads to an increase in the take up of crop insurance by

<sup>&</sup>lt;sup>20</sup>Again we conduct PCA analaysis by sub-treatments. Results are shown in Table ??, Panel B. We find little evidence of a relationship between our measures of control and the interventions.

10.3 pp this is not likely to be working through LOC but other mechanisms.

#### 4.5 Are the null results empirically robust?

In this subsection, we conduct multiple additional robustness tests. All tests in this subsection were not pre-specified in the pre-analysis plan and thus should be treated as exploratory.

First, while we do not find a positive average treatment effect for most of the outcomes, it is plausible that our treatment may vary based on certain farmer characteristics. To test this we utilise the Lasso method to select control variables (see a description of the method in Belloni et al. (2013, 2014)) and analyse possible heterogeneity. In particular, we conduct the standard double lasso outlined in Belloni et al. (2013) to select control variables from a vast set of 118 variables collected at baseline including demographics, agricultural related variables, income and credit, knowledge about insurance and STRVs, risk and time preferences and behavioural and psychological variables. This method allows us to systematically select control variables out of a large set of potential control variables in a way that is consistent, and does not lead to wrong estimates of the standard errors (Belloni et al., 2013). As such we can test the robustness of our treatment variable to systematically selected controls.<sup>21</sup> Note also, by design the double lasso method estimates a lasso regression with the main outcomes y as the dependent variable and another lasso regression with the treatment (usually referred to as d in the literature) as the dependent variable. The latter is akin to a balance test that detects and then select the unbalanced variables accounting for multiple tests (Crépon et al., 2019). Intuitively if zero (or in some circumstances a low number) variables are selected this suggests the treatment is balanced (see Ludwig et al. (2019); Crépon et al. (2019)).

There are two key takeaways. First, consistent with our earlier results, the simulation app has a positive impact on insurance and crop insurance (see Table A4). We also find the information intervention has a positive impact on the use of insurance. We find no other relevant positive impacts on our outcome variables. Second, the double lasso first step, with the treatment as the dependent variable does not select a single control variable out of the 118 possible controls. This suggests that the treatments are balanced.

Next, we consider whether our study has sufficient power to detect effects. To test for this possibility, we calculate the minimum detectable effect (MDE) size of our main estimations (with 80 percent power at the 5 percent significance level)<sup>22</sup> In practice this amounts to just multiplying the standard error of the treatment coefficient by

<sup>&</sup>lt;sup>21</sup>Additional benefits of this method is that it helps select variables that will increase power and the variable choices are made by the algorithm and not the researcher, reducing specification search <sup>22</sup>Wa follow Haush for and Shaning (2016) to calculate the MDE.

the sum of the value of the t-statistic required to obtain 80% (power) and the critical t-value required to achieve a significance level of 0.05. The sample size in the joint agricultural training sample (classroom and edutainment combined along with the pooled psychological intervention) allows us to detect a minimum effect of: 0.151 SD change for the agricultural LOC and 0.103 SD change for the general LOC. The MDE for our other outcomes are: 0.098 SD for insurance, 0.084 SD for crop insurance, 1.77 kgs for fertiliser, 0.580 units of agricultural practice, 0.143 for STRVs and 1.25 units for aspirations. These MDE's are all generally considered small effect sizes, suggesting that this study is not under powered.<sup>23</sup>

It is also important to reiterate here that our sample size is over 10 times larger than the average sample size in the psychology literature for positive psychological interventions (such as self affirmation interventions (see Baranov et al. (2020b)). However, being overly conservative and to help rule out that our results are driven by the size of our sample, we re-estimate our main results using bootstrapping. Bootstrapping allows us to re-sample our data (with replacement) and thus re-estimate the model multiple times to approximate the standard errors.<sup>24</sup>

In summary, these results provide consistent evidence that both the information based psychological control intervention and the joint intervention have no impact on LOC, take up of the two products, agricultural decision making or aspirations and thus has no quantifiable **positive** impact on our outcomes of interest.

## 5 Explanations

In the following section we discuss potential explanations for our results. Since, our results were unexpected we did not pre register analysis studying a null or negative result. As such the analysis below was not included in our pre analysis plan and is exploratory.

#### 5.1 Did the Information Treatment Impact Take Up?

A potentially important issue is whether the information treatment independent of the psychological control intervention impacts knowledge and take up. If the information treatment sans the psychological component does not increase at least knowledge about the two products, then the psychological component has little chance of being effective. In other words, if farmers do not understand how to use or where to buy the prod-

<sup>&</sup>lt;sup>23</sup>The MDEs for the classroom mode of training are: 0.22 for ALOC, 0.15 for GLOC, 0.14 for insurance, 0.13 for crop insurance, 1.92 for fertiliser, 0.381 for Agricultural practices, 0.22 for STRVs and 2.16 for Aspire Yield. The MDEs for the edutainment setting is: 0.21 for ALOC, 0.14 for GLOC, 0.14 for insurance, 0.11 for crop insurance, 2.63 for fertiliser, 0.43 for Agricultural Practices, 0.193 for STRVs and 1.71 for Aspire Yield. Again, these effect sizes are all generally considered small

 $<sup>^{24}</sup>$ We use 2000 repetitions

ucts, then the psychological intervention which encourages use, will have little potential impact. Discussed at length in Yashodha et al. (2021), a subset of farmers were also randomly assigned to a pure control receiving neither the agricultural information or the psychological component. Using this additional sub-sample, we can thus compare this pure no information sample to the agriculture information only sample. At baseline we find that 30.2 percent of farmers were aware of the existence of the agricultural insurance program this was 81% at the endline for those who attended agricultural training.<sup>25</sup> Similarly, in our pure control group only 45% of farmers had knowledge about STRVs while this is 98.6% for those who attended the training. To examine this further, we re-estimate Equation 4.3, but replace the treatment variable with a dummy variable equal to one if the farmer took part in agricultural education (but not the psychological intervention) and zero if they did not receive any education. The results are reported in Table 5.1. As shown in column 9 and 10, the intervention has a large impact on awareness about agricultural insurance and STRVs, the intervention increases agricultural insurance awareness by 26 percentage points and STRV awareness by 56 percentage points. We also find that those in agricultural training are over 7.3 percentage points more likely to use crop insurance. Relative to a baseline rate of 9 percent, this is close to a 80 percent increase. Similarly, STRV use increases by 6 percentage points an increase of over 18 percent. These results suggest that the pure agricultural education intervention had a large positive impact on knowledge and take up. As a result it is unlikely that the null effect of the psychological treatment can be purely explained by a lack of knowledge about the two products.

#### 5.2 The Influence of Covid-19

As the onset of Covid-19 took place when we were halfway through the endline survey, it is plausible that the Covid-19 shock impacted our outcomes or other unobservables in unexpected ways. The Covid-19 pandemic led to multiple government interventions including a strict lockdown. In nearly all districts in our sample individuals were restricted from travelling outside the district and were required to abide by a curfew between 7pm and 7am with restrictions on meeting in large groups. While at the peak of the lockdown in some districts individuals were not able to travel by public transport, there was a closure of all non-essential shops and business, and agricultural activities were banned including harvesting, sowing, and bringing crops to market (note this would have been the following harvest season).

Since the rollout of our intervention was randomised (i.e., the interventions and control took place both before and after Covid-19, in a randomised order), we do not

 $<sup>^{25}\</sup>mathrm{We}$  suspect this is not 100% as some of the endline was conducted close to a year after the intervention was conducted

expect there to be differences in the characteristics of those who received the intervention before and after Covid-19. Although, it is plausible that the effectiveness of our intervention may differ before relative to after Covid-19 and pooling the results may hide this variation. To examine this, we re-estimate Equation 4.3 and Equation 3 but include both a Covid-19 dummy, equal to one if the survey took place after February 2020 and zero otherwise and an interaction between Covid-19 and the intervention variables. Results pooled by training mode are shown in Table 8 and split by classroom and edutainment in Table A3. We find that exposure to Covid-19 changes many of our outcomes (see *PostCovid*). For instance, after Covid-19 exposure, use of STRVs are lower, locus of control is more internal and aspirations about the future are higher. Despite this variation, the effect of Covid-19 does not appear to vary by treatment. There is no significant changes in the interaction terms suggesting that exposure to Covid-19 is not a plausible explanation for our results. Importantly, it also tells us that the intervention does not help those exposed to Covid.<sup>26</sup>

## 5.3 Explanation Behind the Impact of the Simulation App Alone

In contrast to our expectations, the simulation app has a robust impact on the take up of agricultural insurance BUT the treatment with both has little impact on our key outcomes.

One possible explanation is subject fatigue. The treatment with both takes on average around 30-40 minutes longer than the treatment with simulation only. Since the simulation part of the treatment takes place at the end of the experiment it is plausible that in the treatment with both, by the time they reach the simulation app, they are fatigued and have less cognitive bandwidth reducing the absorption of content and the efficacy of information. To test this, we utilise a measure of cognitive capacity –Ravens Matricies–collected during the post-experiment endline survey (after the interventions have taken place), and estimate a regression with Ravens as the dependent variable and the treatments as explanatory variables, we also add a baseline measure of ravens as a control. We argue that if the treatments led to a reduction in cognitive capacity, then those in the treatment with both should have a lower score in the Ravens, controlling for baseline Ravens. Results are reported in Table A10. We find little difference in Ravens score across treatments. This suggests that subject fatigue is not an explanation for this result.

<sup>&</sup>lt;sup>26</sup>We also conducted a phone survey in October 2020, on those not surveyed in the endline before the onset of Covid. However, we found that asking psychological questions was difficult over the phone, we are therefore very skeptical about the quality of the phone survey. Nevertheless, results were very similar to that collected in person.

## 6 Discussion and Conclusion

In this paper we study the relationship between an individuals sense of control and the probability they will adopt new climate resilient practices. We show that the majority of farmers have external control-meaning they think they have little influence on outcomes in general and also in regards to their agriculture. We also conduct a randomised control trial that targets multiple facets of an individuals belief about their ability to influence their agricultural outcomes. In the control treatment, farmers are educated via edutainment or in a classroom setting about agricultural insurance and stress resistant rice varieties. In the treatments they are also exposed to either a psychological control information session, a crop simulation app or both, the interventions are grounded in psychology theory consisting of components that are expected to impact an individuals sense of control. We find that the interventions have no impact on locus of control. Although, we show that the crop simulation app (alone) has a positive impact on the take up of crop insurance, one of our key agricultural products. But other than this positive result, there is little evidence that the information based psychological intervention or both combined influenced agricultural decision-making or aspirations. We conduct multiple robustness tests including multiple hypothesis testing and heterogeneous analysis suggesting we can rule out even modest positive impacts on decision making and aspirations.

Despite our generally non statistically significant findings, we believe this paper is highly relevant in a growing but little researched area in economics. While a number of studies now show that internal constraints are important for decision making in developing countries (e.g., Haushofer and Fehr (2014)), the research trying to move these constraints are still limited. One obvious method is an education intervention targeting these constraints, we do this and show that persistent change is difficult suggesting alternative methods may be needed. However, since the interventions do not effectively change LOC, this means it is difficult to conclusively assess whether changing LOC will impact agricultural outcomes in developing countries.

While there are a number of possible reasons for the general null result, we believe in this case, the interventions which were "light touch", one-time events were not persistent and 'long term' enough to impact behaviour. This is consistent with Baranov et al. (2020b) who conduct a light-touch general psychological well-being intervention and find it had little impact on psychological well-being, beliefs or aspirations. While light-touch interventions have significant benefits including costing less (than longer term interventions) and are more accessible for those who are time poor, our findings suggests that future interventions aimed at an individuals' sense of control may want to test longer term more persistent interventions. This may be particularly true, when individuals are religious like in our sample (as in many developing countries). A strong belief in a higher power implies a relinquishing of personal or internal control and an acceptance of God's will or external control potentially making it hard to change belief about one's control(Akter et al., 2017)<sup>27</sup>. Our findings also suggest that it may not be easy to change peoples beliefs– in developing countries– about their sense of control. However, since this is the first randomised control trial specifically designed to target LOC in a developing country, further research is needed.

Despite the null result in most outcomes, we do find a positive impact of the crop simulation app on take up of crop insurance. This effect, combined with the non existent influence of the interventions on LOC suggests that the crop simulation app must be working through mechanisms other than LOC. We speculate that the crop simulation app may simply be able to provide information in a very simplified more entertaining manner, increasing knowledge absorption. A further limitation is that we are not able to explain why the crop simulation app alone impacts take up of crop insurance but not when combined with the psychological information treatment, further research on the impact of app based gameification may shed light on this result.

<sup>&</sup>lt;sup>27</sup>Increased prevalence of religious and fatalistic beliefs are common in developing countries Schmuck (2000) where people commonly believe that, for example, cyclones are caused by "God's will" and this belief can partly be attributed to abide by God

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**Figure 2:** The Impact of the Joint Psychological Control Treatment Notes: This figure reports coefficients from Table 5 at the 90 percent confidence interval.



**Figure 3:** The Impact of the Psychological Control Treatment: Pooled Notes: This figure reports coefficients from Table 5 at the 90 percent confidence interval.

Variable	All PCI	Control	
	Mean	Mean	p-value
Age	50.892	51.474	0.422
Annual Income (Rs.)	131864.7	128326.9	0.652
Years of Education	5.950	5.950	0.999
Female	0.070	0.055	0.288
Socioeconomic Caste			
General	0.075	0.053	0.111
SC	0.138	0.153	0.438
ST	0.226	0.236	0.664
OBC	0.470	0.471	0.974
SEBC	0.091	0.087	0.822

Table 1: Balance Test

Notes: The Table reports the comparison between the control (agricultural information only) and the pooled psychological control interventions
Variable	Obs.	Mean	SD
Baseline			
Any Insurance	1674	0.250	0.433
Crop Insurance	1674	0.090	0.286
Fertilizer per quintal	1539	14.087	26.657
Age	1674	51.042	13.009
Female	1674	0.066	0.248
Annual Income (Rs.)	1674	130890	141149
Years of Education	1674	5.946	4.587
Endline			
Any Insurance	1674	0.436	0.496
Crop Insurance	1674	0.214	0.410
STRVs	1492	0.322	0.467
Fertilizer per quintal	1539	8.755	8.153
Agricultural Practices	1630	0.522	1.260
Aspired Yield	1140	20.504	4.215

 Table 2: Descriptive Statistics

Notes: The sample is restricted to our main estimation sample

	Agree or		Disagree or
General Locus	Agree	Neither	Disagree
	Strongly		Strongly
I have little control over what happens to me	64%	7%	29%
Luck is very important for what happens in my life	76%	5%	19%
Every time I try to get ahead something someones stops me	59%	11%	30%
Not wise to save cause matter of luck	72%	12%	16%
Not achieved what I deserve	21%	31%	48%
Hard to save for future	83%	5%	12%
Agricultural Locus			
Little control over agricultural production	68%	8%	24%
Luck is very important for agricultural production	79%	5%	16%
Agricultural production does not depend on effort I put in	72%	10%	18%

## Table 3: Descriptive Statistics: Locus of Control

Notes: Panel A reports the General LOC while Panel B reports the Agricultural LOC.

	(1) Insurance	(2) Crop Insurance	(3) Changed Variety	(4) Fertilizer	(5) Log Fertilizer
ALOC	$0.055^{***}$ (0.015)	$0.019^{*}$ (0.010)	$0.007 \\ (0.016)$	-0.431 (0.850)	-0.022 (0.023)
SC	$-0.121^{**}$ (0.051)	-0.060 (0.043)	-0.025 (0.055)	$0.643 \\ (2.114)$	$0.054 \\ (0.078)$
ST	$-0.167^{***}$ (0.050)	$-0.083^{**}$ (0.041)	$0.028 \\ (0.055)$	-2.302 (2.333)	$-0.215^{***}$ (0.083)
OBC	$-0.106^{**}$ (0.049)	-0.071 (0.041)	-0.036 (0.047)	$2.152 \\ (1.712)$	$0.009 \\ (0.067)$
SEBC	$\begin{array}{c} 0.013 \ (0.065) \end{array}$	-0.043 (0.045)	$0.054 \\ (0.060)$	$0.303 \\ (1.624)$	$0.048 \\ (0.073)$
Female	-0.009 (0.034)	-0.013 (0.022)	$0.091^{**}$ (0.045)	$2.150 \\ (2.900)$	$0.067 \\ (0.091)$
Age	$-0.002^{**}$ (0.001)	$0.001 \\ (0.001)$	$0.000 \\ (0.001)$	$0.052 \\ (0.058)$	$0.002 \\ (0.002)$
Years of Education	$0.013^{***}$ (0.003)	$0.007^{***}$ (0.002)	-0.003 (0.003)	-0.083 (0.134)	$0.003 \\ (0.004)$
Log Income	$\begin{array}{c} 0.054^{***} \\ (0.014) \end{array}$	$0.029^{**}$ (0.011)	$0.039^{**}$ (0.016)	-0.654 (0.594)	$-0.059^{**}$ (0.025)
Constant	-0.245 (0.170)	-0.247 (0.129)	-0.178 (0.187)	$18.87^{*}$ (7.516)	$2.888^{***}$ (0.288)
Observations	1674	1674	1674	1590	1543

 Table 4: Baseline Correlations

Notes: This Table reports the relationship between LOC and key outcome variables available at baseline. Standard errors in parentheses \*p < 0.10 \*\* p < 0.05, \*\*\* p < 0.01

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ALOC	GLOC	Insurance	Crop Insurance		Agricultural Prtcs	STRV	Aspired Yield
			Р	anel A: Tr	reatments	Pooled		
All PCI	0.014	-0.021	$0.059^{*}$	0.043	-0.253	-0.160	0.009	0.127
	(0.054)	(0.037)	(0.035)	(0.030)	(0.633)	(0.207)	(0.051)	(0.472)
Constant	-0.010	0.015	$0.394^{***}$	$0.183^{***}$	8.911***	$0.638^{***}$	$0.314^{***}$	20.42***
	(0.047)	(0.030)	(0.029)	(0.024)	(0.564)	(0.010)	(0.044)	(0.391)
Observations	1630	1630	1674	1674	1539	1630	1492	1140
				Panel B:	By Treat	ment		
PCIInfo	0.008	-0.015	0.076	0.045	-0.709	-0.111	0.002	0.856
	(0.066)	(0.046)	(0.043)	(0.036)	(0.670)	(0.639)	(0.061)	(0.625)
Sim. App	0.067	-0.012	0.075	$0.103^{**}$	-0.206	-0.173	0.023	-0.120
	(0.067)	(0.048)	(0.049)	(0.042)	(0.771)	(0.122)	(0.067)	(0.619)
Both	-0.028	-0.034	0.028	-0.011	0.153	-0.196	0.005	-0.314
	(0.065)	(0.047)	(0.043)	(0.035)	(0.807)	(0.114)	(0.062)	(0.614)
Constant	-0.010	0.015	0.394***	0.183***	8.911***	0.638***	0.314***	20.419***
	(0.047)	(0.030)	(0.029)	(0.024)	(0.564)	(0.100)	(0.044)	(0.391)
Observations	1630	1630	1674	1674	1539	1630	1492	1140

 Table 5: ATE Psychological Intervention

Notes: Panel A reports results when the treatments are pooled. Panel B reports results by treatment. Standard errors clustered at the session level. Significance levels: \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

		· · ·	(3) ALOC		(5)ALOC	· · ·
			Freatme			
All PCI					-0.059 (0.095)	
Constant	0.021	0.020	0.005	-0.036	· /	0.056
Training	Pooled	Pooled	Class	Class	Edu	Edu
Observations	1630	1630	803	803	827	827
	I	Panel B	: By Tre	eatment	s	
PCIInfo	-0.024	-0.090	-0.007	-0.049	-0.035	-0.108
Sim. App	-0.003	-0.066	0.020	0.023	(0.121) -0.019 (0.121)	-0.132
Both	-0.087	-0.034	-0.052	-0.043	(0.1121) -0.119 (0.116)	0.005
Constant	$\begin{array}{c} 0.021 \\ (0.062) \end{array}$	$\begin{array}{c} 0.020\\ (0.062) \end{array}$		-0.036 (0.086)	$\begin{array}{c} 0.031 \\ (0.081) \end{array}$	$\begin{array}{c} 0.056 \\ (0.085) \end{array}$
Training	Pooled	Pooled	Class	Class	Edu	Edu
Observations	1630	1630	803	803	827	827

Table 6: PCA-Index Analysis

Notes: This table uses a gricultural locus of control (ALOC) and the general locus of control (GLOC) created using principal component analysis. Standard errors clustered at the session level. Training refers to training mode. In column 1 and 2 we report the training mode pooled, in column 3 and 4 we restrict the sample to the classroom training and column 5 and 6 restricts the sample to the edutainment sample. Significance levels: \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

Treatment	Training	ALOC	GLOC	Insurance	e Crop	Fertiliser	Ag Prtcs	STRVS	s Aspire	
	_	Mode			Insurance	9	-		Yield	
				Panel A:	Pooled Tr	eatments				
All PCI	Pooled	1	1	0.310	0.530	1	0.487	1	1	
All PCI	Classroom	1	1	0.958	1	0.915	0.104	1	1	
All PCI	Edu.	1	1	0.609	0.166	0.933	1	1	1	
			Panel B: By Treatments							
PCIInfo	Pooled	1	1	0.221	0.798	0.923	0.991	1	0.678.	
$\operatorname{Sim} \operatorname{App}$	Pooled	0.955	1	0.442	0.023	1	0.586	1	1	
Both	Pooled	1	0.999	1	1	1	0.279	1	1	
PCIInfo	Class	1	1	0.992	1	1	0.836	1	0.669	
Sim App	Class	0.861	1	0.997	0.954	0.836	0.018	1	1	
Both	Class	1	0.448	0.999	0.996	0.765	0.160	1	0.996	
PCIInfo	Edu.	1	1	0.278	0.401	0.995	1	0.994	1	
Sim App	Edu.	1	1	0.586	0.048	0.927	1	1	1	
Both	Edu.	1	0.994	1	1	0.994	0.994	1	1	

Table 7: P - values from Multiple Hypothesis Testing

Notes: This Table reports p-values for our main estimation using Romano-Wolf method. P-values in bold indicate a  $\rm p_{i}0.05$ 

	(1) ALOC	(2) GLOC	(3) Insurance	(4) Crop		(6) Agricultural	(7) STRV	(8) Aspired
				Insurance	9	Prtcs		Yield
PCIInfo	$0.009 \\ (0.083)$	-0.060 (0.044)	$0.069 \\ (0.068)$	$0.018 \\ (0.048)$	$0.185 \\ (0.695)$	$-0.424^{**}$ (0.209)	-0.030 (0.101)	$1.505 \\ (0.934)$
Sim App.	0.137 (0.098)	$-0.095^{*}$ (0.053)	0.048 (0.088)	0.065 (0.069)	0.423 (1.066)	-0.275 (0.218)	0.039 (0.108)	0.102 (0.865)
Both	$-0.038^{*}$ (0.076)	-0.020	0.005 (0.065)	-0.03 (0.043)	0.725 (0.822)	$-0.381^{*}$ (0.199)	-0.041 (0.097)	(0.803)
Post Covid	$0.371^{***}$ (0.080)		$0.086 \\ (0.058)$	$0.072 \\ (0.047)$	$1.152 \\ (1.104)$	$-0.328^{***}$ (0.189)	$-0.265^{***}$ (0.078)	$1.662^{**}$ (0.739)
PCIInfo× Post Covid	-0.020 (0.116)	$0.076 \\ (0.086)$	$0.009 \\ (0.086)$	$0.046 \\ (0.071)$	-1.725 (1.319)	$0.600^{**}$ (0.243)	$0.089 \\ (0.116)$	-1.186 $(1.250)$
$\begin{array}{l} \text{Sim App.} \times \\ \text{Post Covid} \end{array}$	-0.162 (0.125)	$\begin{array}{c} 0.128 \\ (0.086) \end{array}$	$\begin{array}{c} 0.036 \\ (0.103) \end{array}$	$0.056 \\ (0.087)$	-1.223 (1.581)	$0.247^{*}$ (0.238)	$0.000 \\ (0.123)$	-0.447 $(1.186)$
Both× Post Covid	$0.051 \\ (0.109)$	-0.020 (0.094)	$0.057 \\ (0.083)$	0.061 (0.068)	-1.122 (1.597)	$0.332 \\ (0.215)$	$0.091 \\ (0.111)$	$1.837^{*}$ (1.073)
Observations	1630	1630	1674	1674	1539	1630	1492	1140

Table 8: Covid-19 Analysis: By Treatment: Pooled

Notes: Standard errors clustered at the session level. Significance levels: \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ALOC	GLOC	Insurance	Crop	Fertilizer	Agricultural	$\operatorname{STRV}$	Aspired
				Insurance	9	Prtcs		Yield
				Panel A:	Double La	SSO		
PCIInfo	0.006	-0.014	0.081**	0.050	-0.072	-0.111	-0.011	0.746
	(0.068)	(0.045)	(0.037)	(0.036)	(1.874)	(0.125)	(0.061)	(0.545)
Sim. App	0.070	-0.011	0.098**	0.111**	1.592	-0.153	0.022	-0.289
	(0.068)	(0.047)	(0.039)	(0.040)	(1.624)	(0.118)	(0.068)	(0.575)
Both	-0.042	-0.036	0.029	-0.002	$4.353^{*}$	$-0.171^{*}$	0.001	-0.406
	(0.065)	(0.047)	(0.035)	(0.035)	(2.342)	(0.113)	(0.063)	(0.511)
Observations	1568	1568	1609	1609	1605	1568	1434	1099

Table 9: Robustness: Double Lasso

Notes: This Table reports the impact of the psychological control intervention using the double lasso method; Standard errors clustered at the session level. Significance levels: \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

	(1) ALOC	(2) GLOC	(3) Insurance	(4) Crop Insurance		(6) Agricultural Prtcs	(7) STRV	(8) Aspired Yield
				Panel A	A: Classro	om		
All PCI	0.048 (0.077)	-0.035 (0.055)	0.049 (0.050)	0.000 (0.046)	0.743 (0.687)	$-0.277^{**}$ (0.136)	-0.017 (0.078)	$0.154 \\ (0.770)$
Constant	-0.038 (0.067)	$0.028 \\ (0.045)$	$\begin{array}{c} 0.399^{***} \\ (0.042) \end{array}$	$\begin{array}{c} 0.220^{***} \\ (0.041) \end{array}$	$8.030^{***}$ (0.533)	$0.696^{***}$ (0.125)	$\begin{array}{c} 0.317^{***} \\ (0.069) \end{array}$	$\begin{array}{c} 20.169^{***} \\ (0.655) \end{array}$
Observations	803	803	827	827	755	803	717	538
				Panel B:	Edutainr	ment		
All PCI		-0.003 (0.050)	$0.068 \\ (0.049)$	$0.074^{*}$ (0.040)	-0.978 (0.938)	-0.057 (0.154)	$0.035 \\ (0.069)$	$0.182 \\ (0.614)$
Constant	$0.007 \\ (0.063)$	$0.002 \\ (0.041)$	$\begin{array}{c} 0.390^{***} \\ (0.040) \end{array}$	$\begin{array}{c} 0.159^{***} \\ (0.028) \end{array}$	$9.510^{***}$ (0.858)	$0.600^{***}$ (0.143)	$\begin{array}{c} 0.312^{***} \\ (0.057) \end{array}$	$20.584^{***} \\ (0.482)$
Obs.	827	827	847	847	784	827	775	602
				Panel (	C: Classro	om		
PCIInfo	$0.042 \\ (0.089)$	-0.007 (0.064)	$0.052 \\ (0.060)$	-0.003 (0.054)	-0.170 (0.668)	-0.194 (0.086)	-0.053 (0.096)	$1.324 \\ (0.981)$
Sim. App	$0.113 \\ (0.099)$	0.019 (0.072)	$0.052 \\ (0.069)$	$0.058 \\ (0.058)$	$1.091 \\ (0.915)$	$-0.385^{**}$ (0.154)	$0.018 \\ (0.105)$	-0.126 (0.945)
Both		-0.106 (0.069)	0.044 (0.061)	-0.041 (0.053)	1.427 (1.122)	$-0.276^{*}$ (0.146)	-0.002 (0.089)	-0.720 (0.934)
Constant	-0.042 (0.067)	0.010 (0.045)	$0.400^{***}$ (0.042)	$0.220^{***}$ (0.041)	$8.030^{***}$ (0.534)	$0.696^{***}$ (0.126)	$\begin{array}{c} 0.317^{***} \\ (0.069) \end{array}$	$20.170^{***}$ (0.656)
Observations	803	803	827	827	755	803	717	538
				Panel D:	Edutain	ment		
PCIInfo		-0.023 (0.066)	$0.104^{*}$ (0.061)	0.083 (0.052)	-0.863 (1.070)	-0.041 (0.182)	0.074 (0.090)	$0.446 \\ (0.797)$
Sim. App		-0.039 (0.063)	$0.095 \\ (0.067)$	$0.135^{**}$ (0.061)	-1.190 $(1.134)$	$0.0028 \\ (0.174)$	0.027 (0.086)	-0.070 (0.822)
Both	-0.049 (0.094)	0.051 (0.060)	$0.008 \\ (0.059)$	$0.005 \\ (0.048)$	-0.867 (1.027)	-0.132 (0.163)	$0.011 \\ (0.088)$	$0.185 \\ (0.805)$
Constant	0.0073 (0.063)	$0.002 \\ (0.041)$	$0.390^{***}$ (0.040)	$0.159^{***}$ (0.028)	$9.510^{***}$ (0.859)	$0.599^{***}$ (0.143)	$0.312^{***}$ (0.057)	$20.58^{***}$ (0.483)
Observations	827	827	847	847	784	827	775	602

Table A1: ATE Psychological Intervention

Notes: Panel A and B reports the pooled pooled psychological treatment as the main variable of interest. Panel C and D splits the psychological treatment into its respective parts. Panel A and C restricts the sample to those in the classroom treatment; Panel B and D restricts the sample to the edutainment treatment. Standard errors clustered at the session level. Significance levels: \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	ALOC	GLOC	Insurance	Crop	Fertilizer	Ag.	STRV	Aspired	Aware	Aware
				Insurance		Practices		Yield	Crop Ins.	$\mathrm{STRVs}$
				Panel A: I	Pooled Tra	aining Mo	de			
Ag. Education	0.022	-0.022	0.041	0.079***	0.121	0.058	$0.060^{*}$	-0.248	0.243***	0.556***
	(0.042)	(0.029)	(0.026)	(0.022)	(0.463)	(0.071)	(0.035)	(0.319)	(0.030)	(0.028)
Constant	0.002	0.020	0.389***	$0.152^{***}$	8.693***	0.498***	0.265***	20.61***	0.522***	0.400***
	(0.029)	(0.021)	(0.017)	(0.013)	(0.321)	(0.050)	(0.025)	(0.241)	(0.019)	(0.027)
Obs.	2014	2014	2099	2099	1895	2014	1414	1380	2014	1838
				Panel B	: By Trair	ning Mode	e			
Ag. Education	0.018	-0.011	0.037	0.097***	-0.103	-0.000	0.062	-0.505	$0.251^{***}$	0.563***
in classroom	(0.056)	(0.039)	(0.037)	(0.030)	(0.536)	(0.092)	(0.053)	(0.474)	(0.043)	(0.028)
Ag. Education	0.025	-0.030	0.043	0.066**	0.297	0.103	0.059	-0.058	0.236***	$0.552^{***}$
in Edutainment	(0.052)	(0.036)	(0.033)	(0.030)	(0.634)	(0.093)	(0.045)	(0.419)	(0.037)	(0.030)
Constant	0.002	0.020	0.389***	$0.152^{***}$	8.693***	$0.498^{***}$	0.265***	20.61***	$0.522^{***}$	0.400***
	(0.029)	(0.021)	(0.017)	(0.013)	(0.321)	(0.050)	(0.025)	(0.242)	(0.019)	(0.027)
Obs.	2014	2014	2099	2099	1895	2014	1414	1380	2014	1838

Table A2: The Impact of the Agricultural Training Intervention

Notes: Ag. education is equal to one is a farmer was assigned to agricultural training without any of the psychological interventions, and zero if they were assigned no training at all. Panel A pools the mode of transmission, while Panel B reports the variables of interest by mode. Standard errors clustered at the session level. Significance levels: \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ALOC	· · ·	Insurance	Crop		Agricultural	. ,	Aspired
				Insurance		Prtcs		Yield
				Panel A	A: Classroo	om		
PCIInfo	0.035	-0.035	0.040	0.003	0.203	-0.379	-0.042	0.728
	(0.108)	(0.066)	(0.082)	(0.063)	(0.881)	(0.245)	(0.133)	(1.576)
Sim App.	0.196	-0.059	0.025	0.076	0.565	-0.412	0.178	$-2.512^{**}$
	(0.168)	(0.083)	(0.136)	(0.100)	(1.220)	(0.304)	(0.172)	(1.131)
Both	-0.203	-0.025	0.029	-0.023	1.282	-0.282	-0.071	0.046
	(0.095)	(0.068)	(0.085)	(0.063)	(1.182)	(0.215)	(0.128)	(1.529)
Post Covid	0.346***	0.095	0.063	0.125	-0.518	$-0.593^{***}$	-0.247**	0.592
	(0.115)	(0.090)	(0.088)	(0.085)	(1.075)	(0.220)	(0.111)	(1.208)
$PCIInfo \times$	-0.059	0.031	0.010	-0.035	-0.582	0.455	0.063	0.954
Post Covid	(0.159)	(0.123)	(0.123)	(0.109)	(1.334)	(0.302)	(0.152)	(1.889)
Sim App.×	-0.245	0.078	0.017	-0.072	0.957	0.255	-0.148	-0.489
Post Covid	(0.207)	(0.132)	(0.164)	(0.132)	(1.771)	(0.334)	(0.192)	(1.889)
$Both \times$	0.008	-0.175	0.024	-0.049	0.367	0.078	0.208	$3.748^{**}$
Post Covid	(0.158)	(0.137)	(0.124)	(0.107)	(2.224)	(0.250)	(0.153)	(1.576)
Observations	s 803	803	827	827	755	803	717	538
				Panel B:	Edutainm	lent		
PCIInfo	-0.030	-0.095	0.096	0.028	0.191	-0.479	0.000	2.413***
	(0.120)	(0.058)	(0.107)	(0.071)	(1.138)	(0.338)	(0.150)	(0.813)
Sim App.	0.107	-0.113*	0.068	0.064	0.318	-0.202	-0.048	0.368
	(0.119)	(0.067)	(0.115)	(0.088)	(1.556)	(0.323)	(0.138)	(0.996)
Both	-0.061	-0.017	-0.028	-0.057	0.165	-0.487	-0.001	0.498
	(0.116)	(0.050)	(0.093)	(0.054)	(1.139)	(0.317)	(0.141)	(1.066)
Post Covid	$0.385^{***}$	0.115	0.106	0.051	1.991	-0.648**	-0.288***	0.498
	(0.113)	(0.075)	(0.083)	(0.058)	(1.551)	(0.300)	(0.108)	(1.066)
$PCIInfo \times$	0.048	0.141	0.019	0.103	-1.862	$0.767^{**}$	0.129	$-3.110^{**}$
Post Covid	(0.174)	(0.119)	(0.125)	(0.102)	(2.012)	(0.377)	(0.174)	(1.416)
Sim App.×	-0.090	0.164	0.070	0.151	-2.731	0.314	0.109	-0.141
Post Covid	(0.146)	(0.109)	(0.131)	(0.117)	(2.171)	(0.354)	(0.159)	(1.512)
$Both \times$	0.114	0.172	0.102	0.148	-1.806	$0.608^{*}$	-0.029	0.245
Post Covid	(0.146)	(0.105)	(0.112)	(0.093)	(1.913)	(0.336)	(0.156)	(1.373)
Observations	8 827	827	847	847	784	827	775	602

Table A3: Covid-19 Analysis: By Treatment: Classroom and Edutainment

Notes: Panel A, restricts the sample to those in the classroom treatment; Panel B restricts the sample to the edutainment treatment. Standard errors clustered at the session level. Significance levels: \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ALOC	GLOC	Insurance	Crop	Fertilizer	Agricultural	$\operatorname{STRV}$	Aspired
				Insurance	;	Prtcs		Yield
				Panel A	: Classroo	m		
PCIInfo	0.060	0.013	0.065	0.018	1.020	-0.163	-0.063	1.113
	(0.089)	(0.065)	(0.059)	(0.056)	(1.570)	(0.167)	(0.082)	(0.769)
Sim. App	0.145	0.035	$0.105^{*}$	0.080	4.037	-0.356**	0.036	-0.037
	(0.100)	(0.073)	(0.061)	(0.058)	(2.586)	(0.159)	(0.108)	(0.882)
Both	0.012	-0.090	0.055	-0.043	8.221**	-0.248	0.008	-0.680
	(0.091)	(0.070)	(0.051)	(0.056)	(3.987)	(0.151)	(0.089)	(0.656)
Observations	771	771	794	794	755	771	717	516
				Panel B:	Edutainm	ent		
PCIInfo	-0.040	-0.041	$0.119^{**}$	0.059	3.328	-0.037	0.053	0.204
	(0.105)	(0.065)	(0.047)	(0.051)	(3.731)	(0.175)	(0.091)	(0.706)
Sim. App	0.015	-0.042	$0.088^{*}$	$0.109^{*}$	0.449	-0.007	0.017	-0.524
	(0.092)	(0.059)	(0.052)	(0.057)	(1.962)	(0.168)	(0.086)	(0.781)
Both	-0.082	0.027	-0.013	0.020	1.080	-0.110	0.001	-0.234
	(0.095)	(0.058)	(0.048)	(0.047)	(2.340)	(0.162)	(0.089)	(0.783)
Observations	797	797	815	815	815	797	747	583

Table A4: Impact of the Psychological Control Info. Treatment and crop simulationapp Using Double Lasso

Notes: This Table reports the impact of the psychological control intervention using the double lasso method. Panel A, restricts the sample to those in the classroom treatment; Panel B restricts the sample to the edutainment treatment. Standard errors clustered at the session level. Significance levels: \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

	(1)	(2)	(3)	(4)		
	ALOC	Insurance	-	Fertilizer		
			Insurance	9		
	Panel A: Pooled					
	0.010	0.099	0.014	0 074***		
All PCI	-0.010 (0.039)	0.023 (0.024)	0.014 (0.015)	$3.274^{***}$		
	· /	· /	` '	(1.10)		
t (post)	0.601***	0.160***	0.103***	-2.761***		
	(0.048)	(0.028)	(0.020)	(0.853)		
All PCI $\times$ t	0.022	0.036	0.030	$-3.528^{***}$		
	(0.055)	(0.033)	(0.024)	(1.230)		
Constant	-0.297***	0.233***	0.080***	11.672***		
	(0.033)	(0.020)	(0.013)	(0.690)		
Observations	3304	3348	3348	3273		
		el B: Class		0210		
All PCI	0.061	0.059*	0.009	4.319***		
All PUI	(0.061)		(0.009)			
<i>,</i> , , , , , , , , , , , , , , , , , ,	, ,	, ,				
t (post)	0.543***	0.202***	0.144***	-2.807***		
	(0.079)	(0.044)	(0.034)	(1.088)		
All PCI $\times$ t	0.105	-0.010	$-0.008^{*}$	$-3.575^{**}$		
	(0.088)	(0.051)	(0.039)	(1.610)		
Constant	-0.260***	0.120***	0.075***	$10.837^{***}$		
	(0.058)	(0.030)	(0.020)	(0.855)		
Observations	1630	1654	1654	1535		
		C: Edutai				
All PCI	0.033	-0.000	0.021	2.481		
	(0.049)		(0.021)	-		
t ( t )	( /	× /	· /	. ,		
t (post )	$0.641^{***}$	$0.133^{***}$ (0.037)	$0.076^{***}$	$-2.727^{**}$ (1.291)		
	· /	× /	· /			
All PCI $\times$ t	-0.044	0.068	0.053*			
	(0.073)	(0.045)	(0.031)	(1.736)		
Constant	-0.325***	$0.258^{***}$	$0.083^{***}$	12.237***		
	(0.040)	(0.027)	(0.017)	(1.001)		
Observations	1674	1694	1694	1594		

Table A5: DID Psychological Control Intervention

Notes: This table reports the difference in difference estimates using the baseline and endline. Panel A pools the mode of information transmission; Panel B, restricts the sample to those in the classroom treatment; Panel C restricts the sample to the edutainment treatment. Standard errors clustered at the session level. Significance levels: \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

	(1)	(2)	(3)	(4)
	ALOC	Any	$\operatorname{Crop}$	Fertilizer
		Insurance	Insurance	;
	Pa	anel A: Po	oled	
PCIInfo	-0.018	0.026	0.012	2.310
	(0.046)	(0.030)	(0.019)	(1.416)
Sim. App	-0.002	0.011	0.013	$2.376^{*}$
	(0.048)	(0.030)	(0.020)	(1.360)
Both	-0.010	0.030	0.016	$5.016^{**}$
	(0.047)	(0.029)	(0.019)	(2.039)
Post	0.601***	0.160***	0.103***	$-2.761^{***}$
	(0.048)	(0.028)	(0.020)	(0.854)
$\mathrm{PCIInfo} \times \mathrm{Post}$	0.024	0.050	0.033	-3.020**
	(0.068)	(0.042)	(0.031)	(1.512)
Sim. App $\times$ Post	0.065	0.064	0.090***	-2.583*
	(0.069)	(0.043)	(0.032)	(1.469)
Both $\times$ Post	-0.018	-0.002	-0.027***	-4.863**
	(0.067)	(0.041)	(0.029)	(2.142)
Observations	3304	3348	3348	3129

Table A6: DID Impact by Treatment: Pooled

Notes: This table reports the difference in difference estimates using the baseline and endline. Panel A pools the mode of information transmission. The variable Post refers to the period after the intervention. Standard errors clustered at the session level. Significance levels: \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

	(1) ALOC	(2) Any	(3) Crop	(4) Fertilizer
			Insurance	;
PCIInfo	-0.056	el A: Class 0.076*	sroom 0.010	1.340
1 Olimb	(0.072)	(0.042)	(0.027)	(1.137)
Sim. App	-0.104 (0.076)	$\begin{array}{c} 0.010 \\ (0.043) \end{array}$	$0.001 \\ (0.028)$	$3.736^{*}$ (2.118)
Both	-0.032 (0.073)	$0.080^{*}$ (0.042)	0.014 (0.027)	$7.736^{**}$ (3.327)
Post	$\begin{array}{c} 0.543^{***} \\ (0.079) \end{array}$	$0.202^{***}$ (0.044)	$\begin{array}{c} 0.145^{***} \\ (0.034) \end{array}$	$-2.807^{***}$ (0.913)
$\mathrm{PCIInfo} \times \mathrm{Post}$	$0.094 \\ (0.102)$	-0.024 (0.061)	-0.013 (0.048)	-1.567 (1.191)
Sim. App $\times$ Post	$0.210^{*}$ (0.108)	$0.042 \\ (0.065)$	$0.057 \\ (0.050)$	-2.645 (2.142)
Both $\times$ Post	$\begin{array}{c} 0.032 \\ (0.099) \end{array}$	-0.036 (0.061)	-0.055 $(0.044)$	$-6.308^{*}$ (3.430)
Observations	1630	1654 B: Eduta	1654	1535
PCIInfo	0.014 (0.063)	-0.016 (0.042)	0.018 (0.028)	$3.956 \\ (2.813)$
Sim. App	$0.083 \\ (0.063)$	$0.022 \\ (0.041)$	$0.025 \\ (0.028)$	$1.345 \\ (1.719)$
Both	$0.000 \\ (0.065)$	-0.009 (0.041)	0.021 (0.028)	2.311 (2.113)
Post	$\begin{array}{c} 0.641^{***} \\ (0.060) \end{array}$	$\begin{array}{c} 0.133^{***} \\ (0.037) \end{array}$	$\begin{array}{c} 0.076^{***} \\ (0.025) \end{array}$	$-2.727^{**}$ (1.292)
$\mathrm{PCIInfo} \times \mathrm{Post}$	-0.031 (0.096)	$0.120^{**}$ (0.061)	$0.065 \\ (0.043)$	-4.820 (2.952)
Sim. App $\times$ Post	-0.052 (0.091)	$0.073 \\ (0.058)$	$\begin{array}{c} 0.111^{***} \\ (0.042) \end{array}$	-2.536 $(1.955)$
Both $\times$ Post	-0.048 (0.096)	$0.017 \\ (0.055)$	-0.016 $(0.039)$	-3.177 (2.286)
Observations	1674	1694	1694	1594

Table A7: DID Impact By Treatment

Notes: This table reports the difference in difference estimates using the baseline and endline. Panel A, restricts the sample to those in the classroom treatment; Panel B restricts the sample to the edutainment treatment. The variable Post refers to the period after the intervention. Standard errors clustered at the village level. Significance levels: \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

	(1) ALOC	(2) GLOC	(3) Insurance	(4) Crop Insurance		(6) Agricultural Prtcs	(7) STRV	(8) Aspired Yield
					A: Pooled			
All PCI	$0.026 \\ (0.067)$	-0.054 (0.038)	$0.038 \\ (0.055)$	0.009 (0.039)	0.454 (0.623)	$-0.366^{*}$ (0.187)	-0.015 (0.080)	0.050 (0.684)
Post Covid	$\begin{array}{c} 0.371^{***} \\ (0.080) \end{array}$	$0.106^{*}$ (0.058)	$0.086 \\ (0.058)$	$0.072 \\ (0.047)$	$1.152 \\ (1.103)$	$-0.628^{***}$ (0.189)	$-0.265^{***}$ (0.078)	$1.662^{**}$ (0.738)
All PCI $\times$ Post Covid	-0.034 (0.093)	$0.058 \\ (0.070)$	$0.037 \\ (0.070)$	$0.062 \\ (0.058)$	-1.372 (1.244)	$0.400^{*}$ (0.204)	$0.065 \\ (0.092)$	$\begin{array}{c} 0.211 \\ (0.909) \end{array}$
Constant	$-0.204^{***}$ (0.058)	-0.040 (0.034)	$\begin{array}{c} 0.349^{***} \\ (0.044) \end{array}$	$\begin{array}{c} 0.146^{***} \\ (0.031) \end{array}$	$\begin{array}{c} 8.324^{***} \\ (0.473) \end{array}$	$0.966^{***}$ (0.177)	$\begin{array}{c} 0.438^{***} \\ (0.066) \end{array}$	$19.504^{***} \\ (0.568)$
Observations	1630	1630	1674	1674	1539	1630	1492	1140
				Panel E	B: Classroo	om		
All PCI	0.044 (0.088)	-0.036 (0.060)	$0.032 \\ (0.066)$	$0.007 \\ (0.051)$	$0.700 \\ (0.845)$	$-0.345^{*}$ (0.203)	-0.009 (0.111)	-0.844 (1.126)
Post Covid	$\begin{array}{c} 0.346^{***} \\ (0.115) \end{array}$	$0.095 \\ (0.090)$	$0.063 \\ (0.088)$	$0.125 \\ (0.085)$	-0.518 (1.072)	$-0.593^{***}$ (0.219)	$-0.247^{**}$ (0.110)	$0.592 \\ (1.203)$
All PCI $\times$ Post Covid	-0.073 $(0.135)$	-0.021 (0.106)	$0.016 \\ (0.104)$	-0.039 (0.094)	$\begin{array}{c} 0.207 \\ (1.350) \end{array}$	$0.255 \\ (0.243)$	$\begin{array}{c} 0.069 \\ (0.131) \end{array}$	$1.671^{**}$ (1.420)
Constant	$-0.190^{***}$ (0.070)	-0.015 (0.054)	$\begin{array}{c} 0.371^{***} \\ (0.047) \end{array}$	$0.165^{***}$ (0.040)	$8.253^{***}$ (0.694)	$\begin{array}{c} 0.957^{***} \\ (0.183) \end{array}$	$0.404^{***}$ (0.090)	$\begin{array}{c} 19.93^{***} \\ (0.973) \end{array}$
Observations	803	803	827	827	755	803	717	538
Panel C: Edutainment								
All PCI	$0.007 \\ (0.098)$	-0.072 (0.049)	$0.040 \\ (0.084)$	$0.009 \\ (0.057)$	$0.225 \\ (0.917)$	-0.384 (0.302)	-0.017 (0.112)	$0.954 \\ (0.756)$
Post Covid	$\begin{array}{c} 0.385^{***} \\ (0.112) \end{array}$	$0.115 \\ (0.075)$	$0.106 \\ (0.082)$	$\begin{array}{c} 0.051 \\ (0.058) \end{array}$	$1.991 \\ (1.547)$	$-0.648^{**}$ (0.299)	$-0.288^{***}$ (0.108)	$2.403^{***} \\ (0.809)$
All PCI $\times$ Post Covid	$0.022 \\ (0.127)$	$0.155^{*}$ (0.089)	$\begin{array}{c} 0.070 \\ (0.098) \end{array}$	$0.138^{*}$ (0.078)	-2.148 (1.726)	$0.557^{*}$ (0.320)	$0.070 \\ (0.128)$	-0.877 $(1.094)$
Constant	$-0.215^{**}$ (0.090)	-0.064 (0.043)	$\begin{array}{c} 0.330^{***} \ (0.070) \end{array}$	$0.130^{***}$ (0.046)	$8.387^{***}$ (0.651)	$\begin{array}{c} 0.972^{***} \ (0.289) \end{array}$	$0.468^{***}$ (0.095)	$19.03^{***}$ (0.551)
Observations	8 827	827	847	847	784	827	775	602

Table A8: Covid-19 Analysis

Notes: Panel A utilises the full sample; Panel B, restricts the sample to those in the classroom treatment; Panel C restricts the sample to the edutainment treatment. Standard errors clustered at the village level. The variable Post refers to the period after the intervention. Significance levels: \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ALOC	GLOC	Insurance	Crop	Fertilizer	Agricultural	STRV	Aspired
				Insurance	e	Prtcs		Yield
				Panel	A: Pooled			
All PCI	0.009	-0.021	$0.068^{**}$	0.032	$3.970^{**}$	-0.117	0.020	0.224
	(0.053)	(0.037)	(0.030)	(0.037)	(1.673)	(0.112)	(0.048)	(0.441)
Obs.	1568	1568	1609	1609	1605	1578	1574	1259
				Panel B	: Classroo	m		
All PCI	0.068	-0.018	0.073	0.072	$4.765^{**}$	-0.330**	0.078	1.004
	(0.077)	(0.055)	(0.048)	(0.053)	(2.014)	(0.159)	(0.070)	(0.637)
Obs.	771	771	794	794	790	778	775	609
				Panel C:	Edutainm	ent		
All PCI	-0.033	-0.016	0.061	-0.001	3.945	0.069	-0.015	-0.127
	(0.076)	(0.048)	(0.039)	(0.053)	(2.708)	(0.155)	(0.065)	(0.610)
Obs.	797	797	815	815	815	800	799	650

Table A9: The Impact of the Psychological Control using Double Lasso

Notes: Coefficients reported from a Double Lasso model, we only report the treatment coefficients and not the controls selected as these do not have valid standard errors. Panel A utilises the full sample; Panel B, restricts the sample to those in the classroom treatment; Panel C restricts the sample to the edutainment treatment. Standard errors clustered at the village level. Significance levels: \* p < 0.10, \*\*\* p < 0.05, \*\*\* p < 0.01

Table A10: The Relationship between the Treatment and Ravens

	(1)	(2)
	Ravens	Ravens
	Correct	Correct
All PCI	-0.015	
	(0.152)	
PCI Info		0.115
		(0.203)
Sim. App.		-0.237
		(0.156)
Both		0.062
		(0.197)
Ravens	0.091***	$0.089^{***}$
baseline	(0.031)	(0.031)
Constant	$2.314^{***}$	$2.321^{***}$
	(0.151)	(0.150)
Observations	$1,\!630$	1,630
R-squared	0.008	0.013

Notes: This Table reports the relationship between the psychological treatments and the number of correct responses in the Ravens \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01