

## CASE STUDY 2: ESTIMATING THE IMPACT OF CLIMATE RISK INSURANCE

Why & When to Randomize



Photo: World Food Programme | Benoit Lognone

This case study outlines a hypothetical example of a climate risk insurance program, drawing on real-world impact evaluations of weather-based risk insurance conducted by J-PAL affiliated researchers.<sup>1</sup>

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<sup>1</sup> For further background, see J-PAL's evaluation summaries on [“Examining the Impact of Rainfall Insurance and Family Networks in Burkina Faso”](#) and [“Linking Weather Index Insurance and Credit to Improve Agricultural Productivity in Ethiopia.”](#)

## KEY VOCABULARY

<b>Comparison group</b>	A group that is as similar as possible to the treatment group to be able to learn about the counterfactual. In an experimental design, the comparison group (also called the control group) is a group from the same population as the treatment group that, by random assignment, is not intended to receive the intervention.
<b>Counterfactual</b>	What would have happened to the participants of an intervention had they not received the intervention. The counterfactual can never be observed; it can only be inferred from a comparison group.
<b>Estimate</b>	In statistics, a “best guess” about an unknown value in a population (such as the effect of a program on an outcome) according to a rule (known as the “estimator”) and the values observed in a sample drawn from that population.
<b>Impact</b>	The impact of the intervention is the effect of the treatment. The impact is estimated by measuring the differences in outcomes between the treatment group and the comparison group.
<b>Omitted variable bias</b>	Statistical bias that occurs when relevant (and often unobservable) variables are left out of the analysis. When these variables are correlated with both the primary outcome and a variable of interest (e.g., participation in an intervention), their omission can lead to incorrectly attributing the measured impact solely to the program. For example, omitting socioeconomic status, which is correlated with test scores, could lead to overestimating the impact of a tutoring intervention on a group of high-income students.
<b>Treatment group</b>	The group assigned to receive the intervention.
<b>Selection bias</b>	<p>Bias that occurs when individuals who receive the program are systematically different from those who do not. For example, consider an elective, after school tutoring program. Is it effective at raising children’s exam scores? Comparing scores for those who participate and those who don’t will produce a biased estimate of the effect of the tutoring program if these groups differ across characteristics that correlate with test scores. For example, those who choose to participate may be more motivated and may have scored better than non-participants even without the tutoring program. Randomization minimizes selection bias because it breaks the link between characteristics of the individual and their treatment status. Selection bias can occur in other ways in a randomized evaluation. For example:</p> <ul style="list-style-type: none"> <li>• Participants can choose to take up a treatment or refuse it</li> <li>• Participants can choose to leave the study (i.e., attrit/attrition)</li> </ul>

IMPACT EVALUATION METHODS		
	Method	Description
Randomized Evaluation	Randomized Evaluation/ Randomized Controlled Trial	Measures the differences in outcomes between randomly assigned program participants and non-participants after the program took effect.
Basic Non-experimental Methods	Pre-Post	Measures the differences in outcomes for program participants before the program and after the program took effect.
	Simple Difference	Measures the differences in outcomes between program participants and another group who did not participate in the program after the program took effect.
	Difference-in-Differences	Measures the differences in outcomes for program participants before and after the program <i>relative</i> to non-participants.
More Advanced Non-experimental Methods	Multivariate Regression	Builds on the “simple difference” approach to account for other observable factors that might also affect the outcome, often called “control variables” or “covariates.” The regression filters out the effects of these control variables and measures differences in outcomes between participants and non-participants while holding the effect of the control variables constant.
	Statistical Matching	<u>Exact matching</u> pairs participants with non-participants who are identical based on “matching variables” to measure differences in outcomes.  <u>Propensity score matching</u> uses control variables to predict a person’s likelihood to participate and uses this predicted likelihood as the matching variable.
	Regression Discontinuity Design (RDD)	Eligibility to participate is determined by a cutoff value in some order or ranking, such as income level. Participants on one side of the cutoff are compared to non-participants on the other side, and the eligibility criterion is included as a control variable.
	Instrumental Variables	Uses an “instrumental variable” that is a predictor of program participation and compares individuals according to their predicted participation, rather than actual participation.

## LEARNING OBJECTIVES

- Introduce various quantitative evaluation methods and demonstrate how each method can provide different estimates of impact
- Think critically about the assumptions underpinning different impact evaluation methods
- Provide a deeper understanding of bias and causal inference

## SUBJECTS COVERED

Causality, counterfactual, impact, comparison groups, selection bias, omitted variables, and randomization.

## INTRODUCTION

How can we measure a program's impact and disentangle this from changes in outcomes due to other factors? Ideally, evaluators would do this by following the progress of a group of people as they participate in a program, measure any changes that occur, and then go back in time and measure the same group's progress without the program in place. This second set of outcomes is called the counterfactual. Since we can never observe the true counterfactual, the best we can do is to approximate it.

The central challenge of any impact evaluation is how to identify a valid proxy for the counterfactual. We typically do this by selecting a comparison group who resemble participants as much as possible but who did not participate in the intervention. It is important that the comparison group and the participant group are, on average, as similar as possible, so that we can attribute any differences in outcomes to the intervention rather than other factors. We can then estimate impact by calculating the difference in outcomes observed at the end of the intervention between the comparison group and the treatment group.

An accurate impact estimate can only be attained if the comparison group is a good representation of the counterfactual. If the comparison group poorly represents the counterfactual, then the estimated impact will be biased, leading us to over- or underestimate the true effect. The method used to select, construct, or estimate the comparison group is a key decision in the design of any impact evaluation.

This case study will explore different methods for estimating the impact of climate risk insurance.

## BACKGROUND ON CLIMATE RISK INSURANCE PRODUCTS

Floods, droughts, and other natural disasters present large sources of risk for farmers. Such disasters can lead to a poor harvest, leaving uninsured farming households with little income for the season. In order to cope with unpredictable weather, farmers often plant low-risk, low-return crops instead of investing in more profitable crops that are more sensitive to weather. Farmers who are risk-averse and wary of bad weather may also hesitate to make other investments in their farms such as increasing fertilizer use. As a result, the threat of extreme weather can trap farmers in a cycle of low productivity.

Weather index insurance, which makes payouts to farmers when extreme weather events take place based on observable variables such as rainfall or crop yield, presents one possible solution to help farmers deal

with climate risk. It simplifies the process of verifying insurance claims across many small, fragmented farms by basing payouts on an easily observable variable recorded at a nearby weather station. However, take up remains low and research has shown that farmers are generally unwilling to pay market prices for weather index insurance.<sup>2</sup> This presents an opportunity to conduct research to answer questions around the optimal structure and delivery of insurance programs that aim to help smallholder farmers manage climate risk.

## DISCUSSION TOPIC 1: ESTIMATING THE IMPACT OF CLIMATE RISK INSURANCE

In this case study, we will illustrate and discuss different methods of evaluating impact to try to find a valid proxy for the counterfactual. The impact evaluation methods table at the beginning of this case study may be a helpful reference in answering the questions below.

Imagine you are designing an intervention to test the impact of offering subsidized weather index insurance to farming households on those households' income and food security. In this context, weather index insurance is available to all households at a market rate, but the intervention offers some households the chance to purchase insurance at a lower price. How could we design an evaluation to measure the impact of this subsidized climate risk insurance program on household income and food security? What comparison groups can we use? Complete the table below.

Method	What is the comparison group that represents the counterfactual?	What are potential issues that could lead to bias in our impact estimate with this method?
Pre-post		
Simple difference		

<sup>2</sup> See J-PAL's Policy Insight on "[Protecting farmers from weather-based risk](#)."

Method	What is the comparison group that represents the counterfactual?	What are potential issues that could lead to bias in our impact estimate with this method?
Difference-in-differences		
Statistical matching		
Multivariate regression		
Randomized evaluation		

## INCREASING TAKE UP OF CLIMATE RISK INSURANCE PRODUCTS IN PRACTICE

In practice, many farmers are unwilling or unable to pay market prices for weather index insurance. However, addressing credit, learning, or trust constraints has been shown to improve take up rates in some cases, benefitting both farmers and insurance providers. Interventions evaluated by J-PAL researchers include bundling insurance with subsidies and additional credit products, varying the purchase payment timeline to address credit constraints, and marketing insurance within family networks.

These examples illustrate some potential research questions, such as:

- What is the appropriate subsidy level to promote take up?
- Should we bundle subsidized insurance with other products such as agricultural loans?
- Who should we market insurance to?

In designing an evaluation to answer such questions, researchers and policymakers must consider how the intervention is implemented, what data is available or could be collected, and any practical or ethical considerations in order to identify the most appropriate comparison group and key assumptions to estimate impact.

## DISCUSSION TOPIC 2: THINKING ABOUT WHY AND WHEN TO RANDOMIZE

Farmers generally have to pay for weather index insurance at the beginning of the season, when they may have limited cash on hand. Imagine you have seen that subsidized insurance can improve household income and food security and are aiming to encourage more farmers to take up insurance by offering bundled products.<sup>3</sup> You work on a program that bundles weather index insurance with an agricultural loan that may address farmers' credit constraints and help them to make investments, such as in seeds and fertilizer, early in the season before payouts from the harvest have occurred.

Your organization offers households in participating villages one of the following insurance packages:

- Status quo (insurance available at the market rate)
- Subsidized weather insurance
- Subsidized weather insurance + agricultural loan

You want to evaluate the impact of the bundled program, but it launched last year and you will not be able to randomly assign households in participating villages to different bundles.

2.1 What could be the research question behind this intervention?

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<sup>3</sup> For an example of a bundled intervention in Ethiopia, see J-PAL's evaluation summary on "[Linking Weather Index Insurance and Credit to Improve Agricultural Productivity in Rural Ethiopia](#)."

2.2 How might you evaluate this program as it has been implemented (recall that the program has already launched)? Consider the research method and how to best mimic the counterfactual. What must be true in order for this impact estimate to be unbiased?

Now, consider a new possible intervention your team is planning to launch. In many agricultural contexts, farmers rely on urban-dwelling relatives as a safety net during weather or climate shocks. Imagine you are working on an evaluation that seeks to understand whether marketing insurance to family members, who serve as farmers' de facto safety net, may help address farmers' barriers to taking up insurance themselves.

A previous pilot study in Burkina Faso, where 80 percent of the country's population lives in rural areas and works in agriculture, noted that the number of urban-dwelling relatives reporting that a rural family member asked for money doubled during periods of low rainfall.<sup>4</sup> The study found that 22 percent of urban relatives who were offered a rainfall insurance policy purchased it (a high rate of take up in the typical context of agricultural insurance), and they were more likely to purchase it if the insurance policy specified that compensation would be paid directly to the rural farmer rather than to the subscriber.

Consider how you would go about launching a program to market weather index insurance within family networks and how you might choose to evaluate its impact.

2.3 What could be the research question behind this intervention?

2.4 If you were to design a randomized evaluation to answer this research question, what would you choose for your treatment group(s) and comparison group? What must be true in order for this impact estimate to be unbiased?

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<sup>4</sup> See J-PAL's Evaluation Summary, "[Examining the Impact of Rainfall Insurance and Family Networks in Burkina Faso](#)," and Kazianga and Wahhaj (2020).



## DISCUSSION TOPIC 3: APPLICATIONS TO YOUR WORK

There are many ways to estimate a program's impact and many reasons why we might choose one method over another. Any method relies on the validity of its underlying assumptions and the possible biases or challenges that these assumptions introduce.

3.1 What is an impact evaluation question that is relevant for the programs you work on? How have you tried to evaluate these programs previously and what challenges have you faced?

A randomized design helps ensure that differences in observed outcomes between the comparison and treatment groups are a result of the intervention, instead of a difference in baseline characteristics or other factors during the course of the intervention. However, randomized evaluations also have limitations that should be carefully considered when choosing an impact evaluation method.

3.2 What are political, practical, or ethical considerations that may present challenges to a randomized evaluation of the programs you work on? When do you think it would be appropriate to conduct a randomized evaluation in the context where you work and when would you choose a different evaluation method?

## REFERENCES AND FURTHER READING

Ahmed, Shukri, Craig McIntosh, and Alexandra Sarris. 2020. “The Impact of Commercial Rainfall Index Insurance: Experimental Evidence from Ethiopia.” *American Journal of Agricultural Economics* 102: 1156-76.

Innovations for Poverty Action. “[Marketing Rainfall Insurance to Family Networks in Burkina Faso.](#)” Study Summary.

J-PAL. “[Examining the Impact of Rainfall Insurance and Family Networks in Burkina Faso.](#)” J-PAL Evaluation Summary.

J-PAL. “[Impact Evaluation Methods.](#)”

J-PAL. “[Introduction to Randomized Evaluations.](#)” J-PAL Research Resource.

J-PAL. “[Linking Weather Index Insurance and Credit to Improve Agricultural Productivity in Ethiopia.](#)” J-PAL Evaluation Summary.

J-PAL. 2023. “[Protecting farmers from weather-based risk.](#)” J-PAL Policy Insight. Last updated November 2023.

J-PAL. “[The Advantages of Randomized Evaluations.](#)”

J-PAL North America. “[Common Questions and Concerns about Randomized Evaluations.](#)”

Kazianga, Harounan, and Zaki Wahhaj. 2020. “Will urban migrants formally insure their rural relatives? Family networks and rainfall index insurance in Burkina Faso.” *World Development* 128.

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