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Informed climate adaptation: Input and output subsidies for shaded cocoa

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Informed Climate Adaptation: Input and Output Subsidies for Shaded Cocoa [*]

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Abstract

With growing climate risks, agro-environmental policies seek to protect the environment while reducing poverty by incentivizing climate adaptation. We study how information shapes adaptation under different subsidy schemes for cocoa farmers in Ghana, where forest tree planting for shade is encouraged as an adaptation strategy. Conducting a lab-in-the-field experiment, we compare the impacts of an information intervention under an input subsidy for planting forest trees and an output subsidy for producing cocoa beans from shaded farms. While farmers receiving the information in both subsidy groups plant more forest trees than their subsidy-only counterparts, the increase is higher under the output subsidy than the input subsidy even though the information leads both groups to similarly update their beliefs about the benefits of shade. We rationalize the differential effects of information with a model in which beliefs about rainfall uncertainty and shade benefits affect ex ante input decisions. Counterfactuals show that output subsidy has greater potential to drive adaptation than input when beliefs are reasonably correct. We validate the lab results by distributing tree seedlings, finding consistent treatment effects on the number of seedlings requested and obtained.

KEYWORDS: INFORMATION, SUBSIDY DESIGN, CLIMATE ADAPTATION, COCOA
JEL CLASSIFICATION: Q54, Q56, D24, D83

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1 Introduction

Climate change has intensified the challenges of protecting the environment and reducing poverty in many developing regions, particularly sub-Saharan Africa (SSA), where low-income countries are especially vulnerable to climate risks (Jafino et al., 2020; Jayachandran, 2023).[1] With the majority (54%) of the labor force reliant on rainfed agriculture in SSA, prolonged droughts, extreme heat, and other climate extremes have further reduced agricultural productivity, resulting in lower and more volatile yields in recent years (IMF, 2021; IPCC, 2022).

Addressing these challenges requires effective agro-environmental policies to enhance climate resilience and promote sustainable agricultural practices. Many of these policies fall into the categories of input or output subsidies. Input subsidies are often designed as environmental conservation programs, such as payment for ecosystem services (PES) to promote reforestation, with direct cash transfers to participants engaging in certain environmentally friendly activities. Output subsidies are typically market oriented, such as sustainable certification programs offering price premiums for certified sustainable agricultural products to indirectly subsidize environmentally friendly activities. Examples include Fairtrade certification for various agricultural products and Rainforest Alliance certification for coffee and cocoa products.

However, the relative effectiveness of these subsidies in increasing adaptation depends on individual beliefs. Different beliefs regarding climate risks and impact of adaptation on production may result in different responses to different incentivized subsidy schemes. For example, people whose beliefs heighten their sensitivity to climate risks may respond to input subsidies but not as much to output subsidies, as the prospect of low income and correspondingly low subsidies during a climate-crisis state may overweight the subsidy income they would receive in a normal state. Moreover, shifts in such beliefs may lead to different individual responses. Thus, the role of information campaigns in altering beliefs and thereby improving environmental outcomes is ambiguous.

How do individual beliefs influence the effectiveness of different subsidy schemes in promoting adaptation? Using evidence from Ghana's cocoa sector, we compare the effectiveness

[1] Sub-Saharan Africa is home to 9 of the 10 most climate-vulnerable countries globally (ND-GAIN Index, 2022).

of a standard input-based PES subsidy with an output-based subsidy in incentivizing smallholder farmers' sustainable adaptation, and we explore the role of individual beliefs. Conducting a lab-in-the-field experiment, we investigate whether a subsidy targeting output from sustainable production is as effective at promoting adaptation as an input subsidy that directly compensates for pro-environment activities. We further introduce and assess a narrative-based information intervention on climate risks and adaptation benefits under these two subsidy schemes. To explore the underlying mechanisms, we develop a theoretical model that rationalizes farmers' optimal decisions under the two subsidy schemes and incorporates their beliefs about climate risks and adaptation benefits. This model also guides empirical tests of mechanisms and heterogeneity analysis. Finally, to enhance the lab validity, we examine the effects of lab interventions on farmers' real-life decisions by distributing tree seedlings to lab participants through the Green Ghana Program (GGP), a nationwide reforestation initiative by the Ghanaian government that provides free forest tree seedlings to restore degraded landscapes.

The cocoa industry in Ghana represents an ideal context to compare input and output subsidies, specifically subsidies for trees and subsidies for sustainable cocoa beans relying on trees. Cocoa production is highly vulnerable to climate-related shocks, such as prolonged droughts and irregular rainfall, and saw a global decline of over 10% in the 2023–24 season compared to recent years (ICCO, 2024). As the world's second-largest cocoa bean producer, Ghana relies heavily on cocoa, which employs 17% of the labor force and contributes 3.2% to GDP. In this context, shade management—planting trees around farms for shade—is a key adaptation strategy, as it stabilizes cocoa yields and enhances ecosystem services. Moreover, cocoa farmers hold different beliefs about climate risks and shade benefits, which may influence the relative effectiveness of policies subsidizing sustainable production.

We conduct a lab-in-the-field experiment to examine the impact of two subsidy schemes on promoting shade management. Farmers are randomly assigned into either a control group or one of the two subsidy interventions: the *Input* subsidy, which offers a graduated payment scheme based on the number of forest trees per acre; and the *Output* subsidy, which provides a price premium, increasing in shade level, for cocoa beans produced by shaded farms. The total subsidy income is fixed under *Input* but uncertain under *Output*. A second randomization within each subsidy group assigns farmers to a narrative-based information intervention (*Info*) about increasing climate risks, such as irregular rainfall, and the benefits of shade trees. In the lab, farmers independently participate in two games of shade tree planting and subsidy program participation on a one-acre cocoa plot with land characteristics matched to their own. They are incentivized through cash earnings tied to game outcomes, which are determined by their planting decisions as well as individualized non-tree inputs and simulated climate shocks that mirror real-world conditions.

We conduct the experiment with a representative sample of the universe of cocoa farmers in two areas in Ghana, and we collect data in the field in four rounds. To the best of our knowledge, this is the first study to use the initial cocoa farmer census from the Cocoa Monitoring System (CMS) by Ghana Cocoa Board (COCOBOD) to study responses to adaptation policies. Based on this geocoded census, we selected 30 communities and collected primary data through baseline, lab game, and lab exit surveys. In particular, we measure beliefs before and after the lab experiment to determine potential channels of information effects.[2] Furthermore, we validate the lab outcomes against real-world actions in one of the study areas by distributing tree seedlings under the GGP.[3]

We present our research findings, starting with results from the lab. Comparing the two subsidy-only interventions, we find that the input subsidy has a stronger impact on promoting shade tree adoption. Farmers in the input subsidy (*Input*) group plant 8.3 more forest trees per acre (an 82% increase), while those in the output subsidy (*Output*) group plant 7.6 more trees per acre (a 75% increase), indicating substantial environmental benefits from both types of subsidies. When combined with information nudging, shade tree adoption increases further under both schemes; however, the impact is more pronounced under the output subsidy, closing the gap between the two subsidy-only treatment groups. Specifically, information nudging increases tree planting by 1.4 trees per acre (a 13.8% increase from the control mean) with the input subsidy and 2.4 trees per acre (a 23.6% increase) with the output subsidy, suggesting that the effectiveness of the output subsidy is more sensitive to belief accuracy.

[2]We pre-specify these belief measures in AEA Registry under AEARCTR-0011145.

[3]This follows the official collaboration approval from the Forestry Commission of Ghana in March 2024.

When validating the lab outcomes with farmers' requests for forest tree seedlings under the GGP outside the lab, we observe consistent effects three months after the lab game. Information nudging, particularly when coupled with the output subsidy, leads to a larger increase in the number of tree seedlings requested and obtained, compared the input subsidy. These patterns not only corroborate the lab findings but suggest that incentivized subsidies and information interventions in the lab can translate into farmers' responses in the real world, despite the intervening three months and the fully voluntary nature of the sign-up process.

What drives the varied positive effects of information nudging under different subsidy schemes? We examine the underlying mechanism with a theoretical model of farmers' ex ante optimization over shade trees to maximize expected profit under the two subsidy schemes. The model incorporates farmers' beliefs about climate risks (reflected in beliefs about rainfall) and adaptation benefits (reflected in beliefs about the effectiveness of shade), which jointly shape the production function regarding shade. Subsequently, beliefs influence the optimal number of shade trees in each subsidy scheme, and information nudging has the potential to alter these beliefs. Our model predicts that the role of information under the input scheme is positive but constant, independent of subsidy level. However, the impact of information under output is related to beliefs and can complement the effect of an increase in the subsidy level. When information nudging causes farmers to update their beliefs about rainfall or shade benefits, the resulting adjustment in expected yield influences the rate at which marginal returns to planting shade trees evolve as the subsidy level increases, but only under the output scheme.

We empirically explore which of the belief components—shade benefits or rainfall risks—are shifted by the information intervention following the model prediction. Information nudging increases the likelihood that farmers correctly update their beliefs about shade benefits by 7 percentage points (10% higher than the input-only group), supporting the finding of a positive effect of information nudging under both subsidies. However, we find no evidence of belief updating regarding uncertainty about future rainfall. Besides direct measures of beliefs, we also measure each farmer's perceived optimal shade level under different weather conditions, as optimal shade can be viewed as jointly shaped by beliefs about climate risks and shade benefits. Farmers receiving the information intervention are more likely to increase their perceived optimal shade, resulting in a higher posterior optimal shade level under harsh weather compared to their subsidy-only counterparts.

Additional heterogeneity analysis shows that farmers' prior beliefs about climate risks and shade benefits matter for their ex ante decisions on shade levels. We show that the difference in the effects of the two subsidy-only treatments is mainly driven by farmers who anticipate greater climate risks or lower shade benefits. Farmers expecting more droughts or more unpredictable rainfall plant fewer shade trees under the output subsidy, as they expect to receive lower subsidy income. However, with the information intervention, farmers with these relatively pessimistic beliefs about future climate risks at baseline who are within the output subsidy group respond more to information nudging than their less pessimistic counterparts in the input subsidy group.

Combining the theoretical framework and empirical evidence, we calibrate the model for belief parameters and conduct a counterfactual analysis by increasing the subsidy level. After matching observed and model-predicted moments of average shade tree adoption across treatment groups, we showcase that a 30% increase in the subsidy from the lab levels results in 6.5% higher shade adoption under the output subsidy with information than under the input subsidy with information. This result corroborates the finding that the output subsidy, paired with accurate beliefs, has greater potential to promote adaptation.

Last, we examine the lab treatment effects at the extensive margin on farmers' interest in learning about and enrolling in a similar real-life subsidy program. We find lower demand for output subsidies compared to input subsidies. Farmers' willingness-to-pay (WTP) for enrolling in an output subsidy is 11.5% lower than for a comparable input subsidy. However, information nudging boosts interest in the output subsidy, narrowing the gap between the two subsidy-only treatments. This effect persists three months after the lab as indicated by farmers' expressed interest in a similar subsidy during a follow-up phone survey. Among those interested, information nudging also increases the likelihood of requesting further subsidy details via messages, with no significant differences across subsidy types.

This paper contributes to two main strands of the literature. The first strand is the discussion concerning subsidy policies for carbon reduction and climate adaptation in developing countries. Though the growing literature evaluates the impacts of various PES programs (Alix-Garcia et al., 2015; Izquierdo-Tort et al., 2024; Jack and Jayachandran, 2019; Jack et al., 2022; Oliva et al., 2020) and sustainable certification programs (Bello et al., 2023; De Janvry et al., 2015; Dragusanu et al., 2022; Naegele, 2020) and explores the factors driving their effectiveness, most such studies are program-specific. Aldy et al. (2023) find that an output subsidy is more cost-effective than an investment or input subsidy using a natural experiment on wind farms. We contribute by using a field experiment design to compare output subsidies with input subsidies and by exploring the impact on both environmental benefits and farmer welfare.

We also add to the large and growing literature on climate change adaptation in the agricultural sector (Albert et al., 2021; Bhandari et al., 2022; Burke and Emerick, 2016; Carleton et al., 2024; Kala, 2017; Patel, 2023; Zappalá, 2024). Although the existing literature has focused on the various frictions to adaptation, such as information barriers, credit constraints, and market structure, few studies explore the role of environmental beliefs in individual's adaptation decisions. Patel (2023) and Zappalá (2024) explore the role of farmers' beliefs about flooding or drought in their seed choice and irrigation behavior. We consider a wider range of beliefs, including not only farmers' perceptions of climate risks but their beliefs about how adaptation tools may enter into their production function. Moreover, we connect farmer beliefs to the effectiveness of two types of adaptation subsidies and evaluate how information campaigns that generate updated beliefs may have different impacts on the two types of subsidies.

The remainder of the paper proceeds as follows. Section 2 introduces the background on the two types of agro-environmental policies and the context of cocoa production in Ghana. Section 3 outlines the experimental design and lab-in-the-field game setting. Section 4 details the sampling randomization, data, and empirical specification. Section 5 presents the empirical results. Section 6 develops a theoretical framework to explore mechanisms, with empirical tests and counterfactuals discussed in Section 7. Section 8 discusses other lab outcomes. Section 9 concludes.

2 Background

We study the effectiveness of two types of agro-environmental subsidies—input and output subsidies—in the context of cocoa production in Ghana. Ghana's cocoa production faces climate-induced yield fluctuations. Shade management—planting shade trees on cocoa farms—is widely promoted as a climate adaptation strategy because of its environmental and productivity benefits. Subsidies to encourage shade management may be structured as either input or output incentives, both of which are currently implemented in practice.

2.1 Two types of agro-environmental subsidies

Output-based. Sustainable certification initiatives have gained prominence because of growing consumer demand for environmentally friendly and ethically produced agricultural products. These initiatives certify that farming practices meet specific sustainability standards, which typically results in a price premium for the certified products. In turn, complying farmers also receive a price premium over the market price.

One notable example is the Rainforest Alliance,[4] which offers environmental certification for sustainable practices across various crops, including cocoa, coffee and tea. Rainforest Alliance certification has reached approximately 2.2 million hectares of cocoa production areas and around 1.7 million certified cocoa farmers across 20 countries by 2022 (Rainforest Alliance, 2022). In Ghana, approximately 30% of cocoa production is certified, and certification is often skewed toward larger-scale farms. Certified cocoa producers benefit from a price premium, intended to elevate the living standards of farmers.

To obtain certification, farms must meet the Sustainable Agriculture Standard, which is designed to conserve ecosystems, protect biodiversity and waterways, conserve forests, reduce agrochemical use, improve livelihoods, and safeguard the rights and well-being of workers and local communities. According to the Sustainable Agriculture Standard 2020, certification requirements typically include adherence to environmental standards, fair labor practices, and

[4]In January 2018, the Rainforest Alliance completed its merger with UTZ. UTZ was a program and label for sustainable farming, and the word means "good" in the Mayan language of Quiché. It was reported to be the largest program for sustainable farming of coffee and cocoa in the world.

sustainable farming methods.[5] The process involves initial audits, compliance with set criteria, and ongoing verification to maintain certification status.

Input-based. Most current PES subsidies for forest trees can be seen as input subsidies when they target farmers to promote sustainable agriculture. These policies directly incentivize actions that provide ecological benefits, such as planting trees or maintaining natural habitats.

A notable input-based PES scheme is the Reducing Emissions from Deforestation and Forest Degradation (REDD+) program. REDD+ aims to mitigate climate change through forest conservation, sustainable management, and enhancement of forest carbon stocks. Recently, Ghana received a substantial REDD+ payment in recognition of its efforts to curb deforestation and forest degradation. In 2023, the World Bank's Forest Carbon Partnership Facility (FCPF) awarded Ghana $50 million for reducing carbon emissions by 10.24 million metric tons between 2019 and 2021, based on verified carbon reductions from tree planting. The funds received from REDD+ are reinvested in furthering sustainable land-use practices, including agroforestry and improved agricultural techniques, which directly benefit cocoa farmers.

2.2 Cocoa production

While cocoa is the most important cash crop in Ghana,[6] its production is highly vulnerable to climate change-related shocks. Therefore, planting trees on cocoa farms for shade and yield stabilization (so-called *shade management*) is encouraged as an adaptation strategy.

Global cocoa production has seen significant fluctuations due to drought and irregular rainfall patterns. For example, extremely hot weather can make cocoa trees wilt, while early onset of rainy season may wash off fertilizers and reduce pollination of cocoa flowers (Fountain and Huetz-Adams, 2022). In the 2023–24 season, the global cocoa supply experienced an over 10% decline compared to recent years (ICCO, 2024). In Ghana, the cocoa bean harvest fluctuates significantly over time and across regions (Figure B.1).

[5]The Sustainable Agriculture Standard 2020 includes two constituent parts: the Farm Requirements and the Supply Chain Requirements. More detail is available at https://www.rainforest-alliance.org/resource-item/rainforest-alliance-sustainable-agriculture-standard-introduction/.

[6]See https://opecfund.org/news/ghana-is-cocoa-cocoa-is-ghana.

Despite the global fluctuations in cocoa yield and prices, the COCOBOD sets a fixed domestic cocoa price every year and commissions a number of private cocoa purchasing companies to purchase cocoa beans at the specified price from farmers. Therefore, cocoa farmers' exposure to climate change risks is limited to yield fluctuation. To maintain cocoa production, COCOBOD offers training and resources through its Cocoa Health and Extension Division (CHED), including training on climate-smart technologies, annual spraying of pesticides, and farming guidance by extension agents.

2.3 Shade management as an adaptation strategy

Shade management involves planting forest and fruit trees among cocoa trees to provide shade,[7] offering both social and private benefits. Social benefits include carbon sequestration, biodiversity conservation, and ecosystem services (Blaser et al., 2018; Jezeer et al., 2017; Tschora and Cherubini, 2020). According to Forest Carbon Partnership 2021, one extra forest tree can capture 8–14 kg carbon dioxide per year. At a price of USD 66 per ton of carbon dioxide, this translates into USD 13–23 for a one-acre cocoa farm with high shade (25 forest trees). Since the social cost of carbon is well above the prevailing market price of carbon, the social benefits may be even larger. Private benefits for farmers stem from improved cocoa production of shaded farms for reasons including better microclimate conditions for farms, retained ground water, reduced vulnerability to diseases (Andres et al., 2018), and increased resilience against extreme weather events such as prolonged drought (Tscharntke et al., 2011). Therefore, yields are stabilized across weather conditions when farms are under proper shade management.

In Ghana, despite the nationwide guideline set by the COCOBOD recommending the maintenance of 16 shade trees per acre,[8] shade management practices vary widely among cocoa farmers. Figure 1 illustrates the variation in shade levels, showing that farmers maintain 9 shade trees per acre on average, far below the recommended level.

[7] Temporary shade plants such as plantains and bananas are not considered shade trees as they can only provide shade for young cocoa seedlings and are typically removed after six months.

[8] COCOBOD recently increased the recommended shade level from 6–8 trees per acre to 16 trees per acre, based on findings from the Cocoa Research and Extension Technical Committee. This updated recommendation was initially presented at the COCOBOD national forum in November 2023 and revisited in July 2024, with participation from policy makers and experts from COCOBOD, the Forestry Commission of Ghana, and the World Bank.

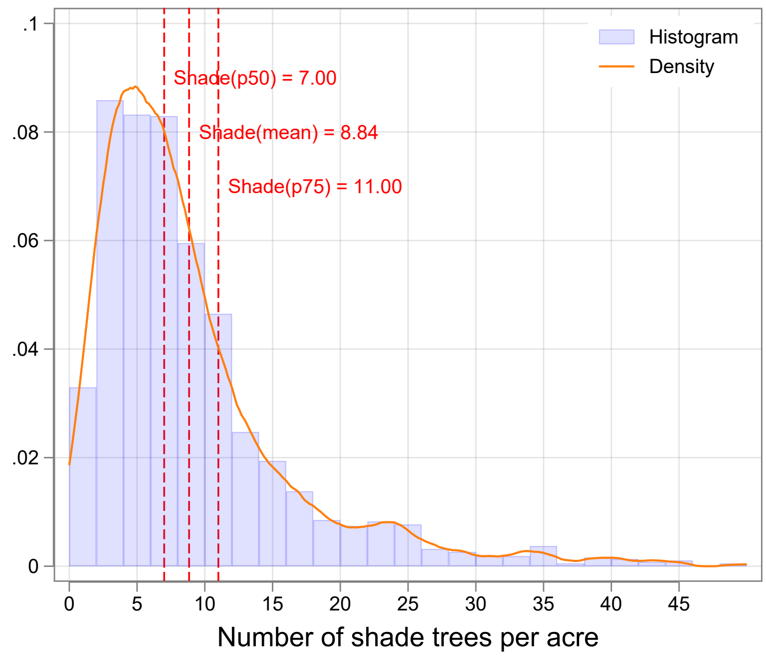


Figure 1: Distribution of shade levels

Notes: This figure presents the histogram and probability density of shade level of sampled farmers' main plot, defined by number of shade trees per acre, according to self-reported number of shade trees (including forest trees and fruit trees) and land size in the baseline survey.

Adoption of shade management practices is influenced by various factors, including access to training and resources provided by COCOBOD. Training programs focus on enhancing farmers' literacy regarding climate-smart technologies and sustainable agricultural practices. These programs aim to increase farmers' understanding of the benefits of shade management and encourage the adoption of practices that can improve both environmental sustainability and economic resilience. Around 56% of cocoa farmers have ever attended at least one relevant training program on shade management.

3 Experiment

We conduct a lab-in-the-field experiment designed to mirror farmers' real-world decisions about subsidy program participation and shade tree adoption under varying subsidies and information interventions. Eligible farmers were randomly assigned to a control group or one of two subsidy interventions—the *Input* subsidy or the *Output* subsidy—to assess the subsidies' effectiveness in promoting forest tree planting, given farmers' prior beliefs. Within the two subsidy groups, we further randomized farmers into an intervention with narrative-based information about increasing climate change risks and the benefits of shade trees to examine the role of updated beliefs in improving efficacy given various subsidies.

After randomization, farmers are asked to play two games on a hypothetical one-acre cocoa plot. In each game, farmers are asked to consider a hypothetical cocoa plot and given 500 initial tokens to be spent on shade tree planting and enrollment in the potential subsidy program (if applicable). They are provided with relevant cost information and plot and weather conditions. We instruct farmers to rely on their own knowledge of cocoa production functions to maximize their expected income considering different weather conditions and certain subsidies. After completing the game, farmers earn cash rewards in Ghanaian cedis based on their gains from their hypothetical cocoa harvest and any subsidies from a randomly selected game at a rate of 100 tokens per cedi.

In the following sections, we first introduce the two subsidy interventions and the information intervention. Then, we present an overview of the lab-in-the-field game setting. Lastly, we briefly discuss the validity of the game design.

3.1 Subsidy interventions: *Input* vs *Output* subsidies

We consider two types of subsidy interventions. The *Input* subsidy applies a graduated lump-sum payment scheme increasing in shade level as measured by number of forest trees. The *Output* subsidy offers a variable price premium for cocoa beans harvested from certified farms, increasing in shade level, with total subsidy income undetermined. As shown in Table 1, both subsidies are based on four shade levels determined by number of forest trees per acre and increasing from Not Qualified (0–6 trees/acre) to High (19–25 trees/acre). Any farms with over 25 forest trees per acre are identified as High level. The highest price premium under the *Output* subsidy is 12.5%, which is similar to that of existing certification initiatives such as the Rainforest Alliance.

Unlike the *Input* subsidy, for which the total subsidy income is fixed given the shade level, the total subsidy benefit that respondents can earn under the *Output* subsidy is determined by both the price premium (varying by shade level) and the cocoa bean harvest, resulting in some income uncertainty. For a farmer with average productivity,[9] the expected subsidy income from both subsidies is almost equivalent.[10]

To obtain the potential subsidy benefits under either of the two subsidy programs, respondents are required to pay 70 tokens upfront to enroll in the given subsidy program. The enrollment fee is not refundable. To ensure the respondents understand the subsidy programs, they are guided through a card illustrating the given subsidy option during the lab session, as depicted in Appendix Figures B.3a and B.3b.

Table 1: Four-tier *Input* and *Output* subsidy schedule in the game

Shade level		***Input* subsidy**	***Output* subsidy**	
Label	Forest trees/acre	Lump-sum payment	Cocoa price/bag	Premium
High	19–25	220	900	12.50%
Medium	12–18	130	870	8.75%
Low	7–11	75	840	5.00%
Not Qualified	0–6	0	800	0.00%
Other prices (tokens)				
Beginning balance			500	
Standard price/bag			800	
Cost/tree			5	
Subsidy enrollment fee			70	
Baseline average yield (bags/acre)			1.8	

Notes: This table outlines the four-tier subsidy schedule under the *Input* and *Output* subsidies, together with other game components.

3.2 Narrative-based information intervention

To further explore the effectiveness of information nudging under different subsidies, we cross-randomize the two subsidy treatments with a narrative-based information intervention. The intervention allows us to investigate the effect of updating individual beliefs on target policy outcomes as well as possible mechanisms.

[9]Based on sampled farmers' self-reported cocoa harvest in 2022 and 2023 in the baseline survey, the average productivity is 1.79 bags/acre.

[10]In Appendix Figure B.4, we show that farmers with average productivity under each shade category can obtain similar expected subsidy income under the *Input* and *Output* subsidies.

The information treatment includes information concerning increasing climate change risks and the benefits of shade.[11] On climate change risks, the information describes the key risks in Ghana including irregular rainfall patterns with greater variability, increasing water stress, and shortening growing seasons. On shade tree benefits, the information shows that more shade trees on farms can help farmers adapt to climate change by curbing the cocoa production decline due to the harsh weather and can offer additional ecosystem services such as biodiversity.[12] The script is validated and translated into the local language, Twi, by local scientists from the Rainforest Alliance and experts from COCOBOD.

The information is delivered after setting the scene for the hypothetical growing conditions and before introducing the subsidy details. Therefore, the information is given before the comprehension test and both decision-making games. Instructors were trained to disseminate the information to respondents strictly following the written scripts in Twi, the most common local language.[13] Meanwhile, an enumerator is sitting next to each farmer and pointing at the corresponding illustration (Figure B.3c) as a prompt to ensure full attention and engagement.

We design the information treatments with two potential channels in mind. First, the information on climate change risks may change farmers' beliefs about the likelihood of extreme weather conditions. Since most farmers have some prior knowledge of shade management, this shift in beliefs may in turn affect the value of precautionary measures such as planting shade trees. Second, the information on shade tree benefit may directly shift farmers' belief about the value of shade trees, including private benefits under harsh weather and positive externalities. While we cannot decompose the impact of information into these two channels, we test whether the corresponding beliefs are shifted by the information. If so, leveraging the exogenous information shock shifting farmers' beliefs, we can compare farmers' decisions with or without information for each subsidy intervention. We evaluate whether and how much the effectiveness of subsidy interventions on shade adoption depends on correct beliefs.

[11] The full script can be found in Appendix A.

[12] Notably, the information about shade tree benefit is qualitative. We do not provide quantitative information, such as the optimal number of shade trees.

[13] In both Nkawkaw and Sefwi Bekwai, the instructor delivering this information is one of the two well-trained enumerators, and the instruction takes place in person.

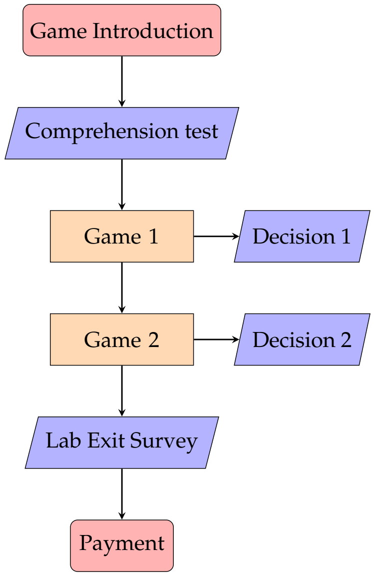
3.3 Overview of the lab-in-the-field game

In this section, we outline the lab-in-the-field game setting, introducing the incentivized decision-making process, game-flow, and payment structure. Figure 2 shows the game flow diagram and an example of how land information is presented to farmers.

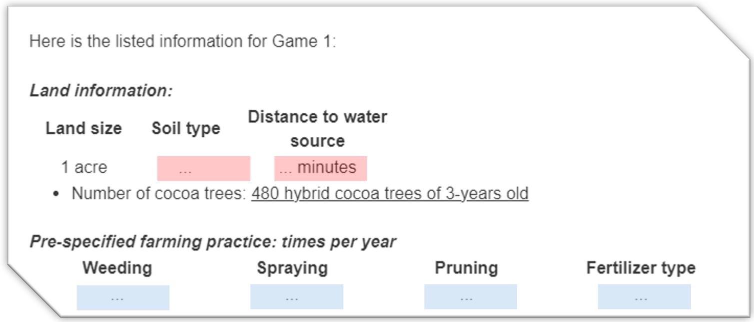
Incentivized decisions. Farmers from the same treatment group within each community are invited to attend the same lab session, in which they are introduced to the game mechanics. In the lab session, each farmer independently decides on shade tree levels (including number of forest and fruit trees) and whether to participate in the subsidy programs (if applicable) for a hypothetical one-acre cocoa plot in two separate games. They start with 500 tokens in each game, which they can allocate toward planting trees, enrolling in subsidy programs, or saving for profit, given associated price and cost information. Farmers rely on their own knowledge of production functions to maximize their end-of-game payment. All decisions are made independently, with no interaction permitted between farmers. Farmers are rewarded with cash based on their gains from a randomly selected game; the reward includes cocoa-harvest income and subsidies, with 100 tokens equaling 1 cedi.

Game introduction. The lab session starts with a detailed game introduction by a moderator, which covers (1) the process for determining postgame payments; (2) the key decisions each farmer needs to make in each game, along with relevant price and land information; and (3) details on any applicable subsidy programs and information interventions. A comprehension test follows to confirm farmers' understanding of the game.

Farmers are informed that the cocoa bean harvests in each game are determined by a pre-trained production function. This function incorporates factors such as the number of forest and fruit trees planted, land characteristics, farming practices, and predetermined random weather and disease shocks. The production function is developed using detailed information from the farmers' actual cocoa plots. Therefore, farmers should make game decisions regarding shade levels and subsidy program enrollment (if any) using their best knowledge of their own production function, as if in real life. To prevent farmers from learning about the production function during the game, harvest results are disclosed only after both games are completed. The pre-



a. Flowchart



b. Example of game card: listed land information

Figure 2: Flowchart of lab session and example of land information

Notes: This figure illustrates the main components of the lab-in-the-field game (Panel (a)) and an example of how land information is presented to respondents during a game (Panel (b)).

dicted production function is trained using machine learning tools, leveraging all sampled cocoa farmers' geocoded real plot information, including land characteristics, farming practices, number of shade trees, and weather conditions (i.e., temperature, precipitation).[14]

Games. After the introduction, farmers enter into two games in sequence. Each game starts with 500 initial tokens, which can be used for planting shade trees, enrolling in the given subsidy program (if any), or saving for end-of-game profit. The unit cost per (forest or fruit) tree is 5 tokens, and a nonrefundable upfront cost of 70 tokens is required to enroll in any subsidy programs (if applicable).[15] Each game features variable land information, including land characteristics and other prespecified farming practices (Figure 2b). Farmers decide on subsidy enrollment and tree planting (number of forest and fruit trees) based on these factors. Their final token count reflects both the costs of planting shade trees and enrolling in subsidy programs, and the earnings from cocoa bean harvests. The earnings per game are based on a fixed price

[14]We used Linear Discriminant Analysis (LDA) as the classifier to predict production per acre for each respondent. Appendix B.9 shows the cross-validation scores of different machine learning models. We selected this classifier because of its high accuracy and relatively narrow confidence interval.

[15]The maximum number of trees they can plant is 100 if not enrolled in a subsidy, or 86 if enrolled.

of 800 tokens per bag of cocoa beans, with potential bonus payments depending on the shade tree levels they select (as outlined in Section 3.1). These token values reflect real-world cocoa prices,[16] transportation and maintenance costs of planting trees, and membership fees for co-operative registration, providing a realistic cost-benefit scenario. All relevant price components are summarized in Table 1.

Payment. After both games and a lab exit survey, harvest results for both games are revealed. One of the two games is randomly selected for payment. Farmers receive cash in cedis based on the greater value between the initial 500 tokens and the final tokens from the selected game, with an exchange rate of 100 tokens to 1 cedi. The final token count incorporates the costs and earnings associated with cocoa harvests, reflecting decisions made regarding tree planting and subsidy enrollment, as well as other predetermined factors used in the predicted production function.

3.4 Game validity

We incorporate various design features into the lab-in-the-field game to address potential biases and maximize data quality, enhancing its validity.

First, to address potential biases stemming from farmers' varying familiarity with land characteristics, each farmer plays two games on hypothetical plots in a randomized order. One plot has uniform, prespecified conditions shared across all farmers, while the other is based on an individual plot randomly selected from each farmer's actual cocoa-plot data collected during the baseline survey. To maintain balance across the two games, farmers are not informed that which plot is based on their actual farm. Additionally, we randomly select one game for payment to mitigate concerns that paying for both games might incentivize strategic hedging behavior, especially if farmers are uncertain about the production function.

We also take several measures to ensure the quality of the data collected in the lab. First, to confirm that farmers understand the process for determining their game earnings, we provide a detailed example of the payment calculation during the introduction, followed by a similar

[16]The producer price for one bag of cocoa beans (64 kg) in the 2022–23 season was 800 Ghana cedis.

exercise in the comprehension test. Enumerators demonstrate this calculation multiple times, ensuring that farmers can accurately explain the process themselves. Second, we emphasize that the best decision-making strategy in the game is to rely on knowledge gained from real-life experiences. Third, to facilitate comprehension, each farmer receives a set of illustrated sheets, and enumerators guide them through comprehension questions before decisions are made. Finally, to maintain focus and prevent interaction between respondents, we assign one enumerator for every two farmers throughout the session, allowing them to address any questions that arise during the games.

The lab setting simplifies the farming decision-making process by controlling other farming practices at prespecified levels. Farmers' decisions regarding shade tree planting are thus interpreted as their best response to the predetermined factors and available subsidy programs. By fixing land characteristics and prespecified other farming practices, we isolate the influence of competing factors, allowing for a clearer evaluation of how subsidy programs affect tree planting behavior.

4 Data and empirical specification

In this section, we introduce the sampling, intervention randomization and data collection process, and then show our empirical specification.

4.1 Sampling

The study includes 30 communities in Ghana, with 20 from the Nkawkaw district of the Eastern Region and 10 from the Sefwi Bekwai district (or Sefwi) of the Western North,[17] as shown in Appendix Figure B.2. The selection of these communities was based on an administrative list of cocoa farmers registered in the Cocoa Monitoring System (CMS),[18] which is the first nationwide census of cocoa farmers in Ghana and was initiated in 2019 to improve co-

[17]Region selection followed COCOBOD's recommendation: Nkawkaw is the largest cocoa-growing community in Ghana's Eastern Region, the original site of cocoa cultivation in the country; Sefwi is one of the traditional cocoa growing regions with suitable growing conditions.

[18]In August 2022, we obtained formal written approval from the chief executive of the Ghana Cocoa Board to conduct field research and acquire data support in the sample districts.

coa traceability. The CMS includes details about each farmer's unique cocoa ID, community, operational area[19] and geocoded cocoa plots. We assessed community size by the number of CMS-registered farmers and then randomly selected one community per operational area. This process resulted in a total of 30 communities, representative of 24,868 farmers across 312 communities in our study regions.

We restricted the sample to large ($\geq$ 90 registered farmers) communities to ensure at least 72 eligible farmers per community for the lab-in-the-field game, in turn mitigating the effect of potentially low baseline survey response rates.[20] Additionally, we selected only one community per operational area to enhance geographic variation, improve sample representativeness, and mitigate potential bias from local extension agents assigned at the operational area level. As shown in Figure B.2b, the 30 selected communities are widely distributed, with differential geographical characteristics and climate risk exposures.

Cocoa farmers were eligible for this study if they were 18 to 75 years old, possessed at least one cocoa-dominated plot, had at least 3 years of cocoa-growing experience (ensuring at least 1 year of harvest), and made independent farming decisions. The focus on decision-making independence identifies these farmers as the primary agents exposed to climate risks, responsible for adaptation choices and bearing the consequent profits or losses. We excluded farmers over 75 years old, as their production choices may be less representative because of potential health issues. Further, given the long-term nature of cocoa yields and shade tree benefits, which extend over 20 years, elderly farmers may consider additional factors that are less relevant to most cocoa farmers. We also excluded farmers whose primary income source was non-farming activities, as they are less vulnerable to climate-induced income shocks. By focusing on farmers primarily reliant on cocoa farming, this study aims to provide insights into adaptation strategies among those most vulnerable to climate change.

To maintain our focus on smallholder farmers, we further excluded from the baseline survey eligible cocoa farmers who were in the top 1% either by number of cocoa plots owned or

[19] The Cocoa Health and Extension Division district offices of COCOBOD establish operational areas for management and training purposes. Each operational area encompasses multiple communities and is overseen by an extension agent responsible for primary training and other professional services.

[20] The sampling strategy anticipated over 10% attrition in the baseline survey, as contact information was missing for over 30% of registered cocoa farmers in the CMS data.

by total plot size. This resulted in 1,905 farmers qualifying for randomization across treatment arms for the lab-in-the-field game.[21] Focusing on smaller-scale farmers is essential, as those with larger cocoa plots are likely to have access to different production resources and adaptation strategies.

4.2 Stratified randomization

Stratified randomization was conducted at the farmer level, first by community, considering distinct community characteristics such as farmer groups and shared farming assets such as spraying machines. Additional stratification by gender, age (55+ years or older), and land size (five acres or more) accounted for differences in adaptive responses. Each eligible farmer was randomly assigned to one of five treatment arms based on (1) the subsidy intervention (control, *Input*, or *Output* subsidy) and (2) the information intervention within subsidy groups (information control or narrative-based intervention). This randomization resulted in five treatment arms: *Control*, *Input*, *Output*, *Input+Info*, and *Output+Info*, as shown in Figure 3.

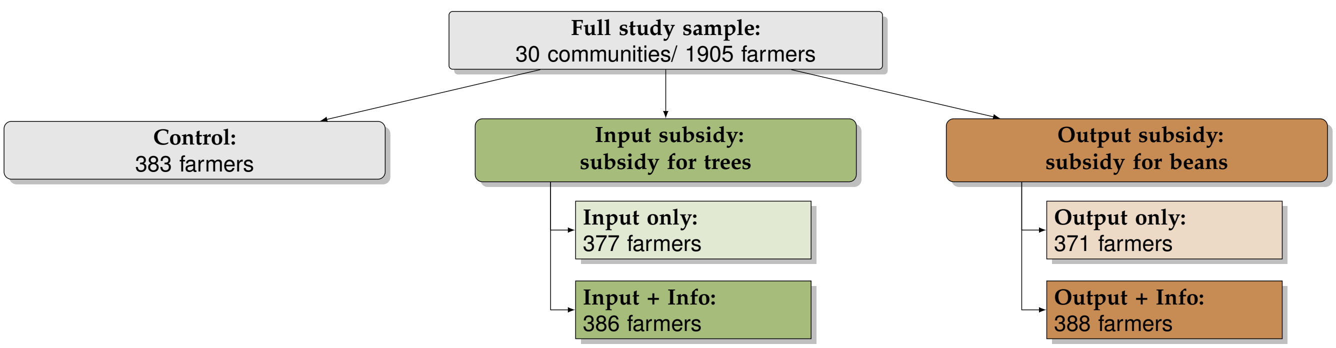


Figure 3: Randomization design across treatment arms

Notes: This figure depicts the random assignment of eligible farmers across five treatment arms.

4.3 Data description

We conducted four rounds of data collection to support our empirical analysis: a baseline survey, a lab-session survey (including game responses and a lab exit survey), a phone survey, and distribution of forest tree seedlings. The first two rounds took place in both Nkawkaw and

[21] As shown in Appendix Table B.3, the initial sampling frame for the lab game included 1,929 farmers, with 24 farmers not attending (an attrition rate of 1.2%).

Sefwi, while the last two were conducted only in Sefwi. Figure 4 presents the timeline of data collection, conducted separately in each district: Nkawkaw in 2023 and Sefwi in 2024. Baseline surveys were conducted between February and March each year, followed by lab-session surveys in March and April. In June 2024, we conducted the phone survey and distributed forest tree seedlings for the GGP in Sefwi.

Our main analysis relies on the first two rounds of data collected in both regions. The additional rounds, focusing on forest tree requests for the GGP and demand for similar subsidy programs, serve to validate the lab outcomes.

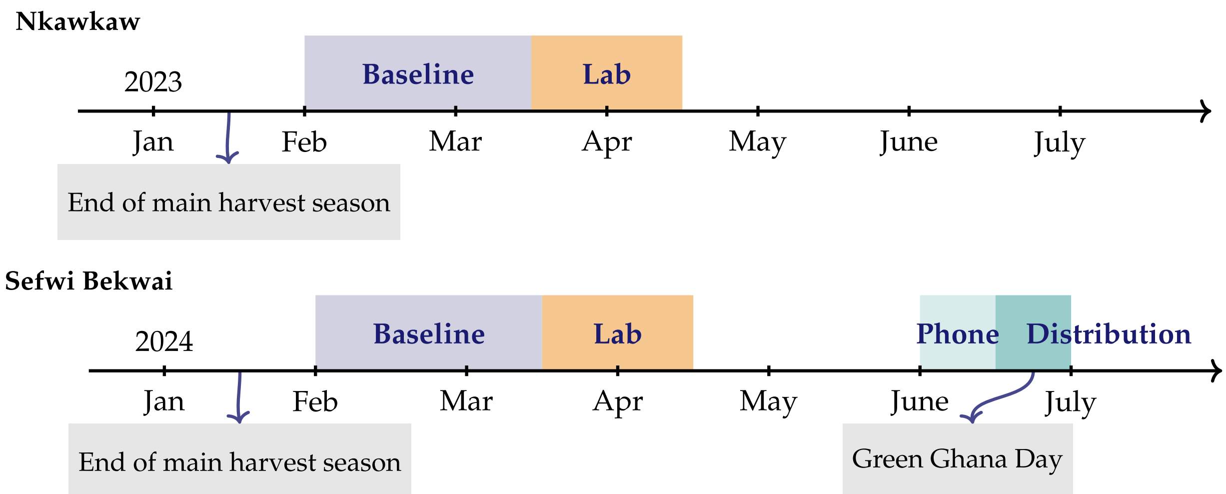


Figure 4: Timeline of data collection activities

Baseline survey. The baseline survey collected both plot- and individual-level data for each eligible cocoa farmer. Plot-level data covered land characteristics, shade practices and other inputs, farming activities (for example, fertilizer use, weeding, spraying, pruning), and yields. At the individual level, we gathered bio-data and data on education, cooperative membership, income-generating activities, and household characteristics. Additionally, we collected information on climate-smart agricultural training, cocoa certification experience, and past GGP involvement. A key component was an independent module on farmers' beliefs about climate risks, shade practices, and the impact of these factors on cocoa production, introduced in detail in Section 7.

Lab-session survey. The lab-session survey encompassed data collection during the lab game and a postgame lab exit survey. During the game, we recorded each farmer's responses, including participation in any subsidy program and the number of forest and fruit trees they decided to plant—key data for evaluating the impacts of both subsidy and information interventions. The lab exit survey repeated belief questions from the baseline and gathered data on farmers' intentions to sign up for forest tree seedlings in the upcoming GGP, as well as their WTP for similar subsidy programs if implemented in real life. These measures support the validation of the lab outcomes and corroborate the findings across the extensive and intensive margins.

Phone survey and distribution. In the phone survey, we again asked each farmer about their tree seedling requests for the GGP in 2024, informing them that this information would guide real-world seedling distribution and allowing them to adjust their initial responses. We also inquired about their interest in a similar real-life subsidy program by gathering responses both during the call and through voluntary follow-up messages from farmers seeking more details, with the program type aligned to their lab-assigned subsidy interventions. Additionally, we collected data on each farmer's travel time from their home and cocoa farms to the community assembly point to capture transportation costs. On distribution day, we recorded each farmer's attendance, actual number of seedlings received, and pickup method (personal collection or collection by an agent).

Sample descriptives. Our sample broadly represents the cocoa farming population in these two regions, according to CMS records. Baseline summary statistics are as follows: 40% of the sample are female, with an average age of 52 years and 18 years of cocoa farming experience. Education levels are generally low, with only 10% having attained high school. On average, farmers own two cocoa plots totaling six acres, yielding 1.79 bags (115 kg) per acre. Annual income from the primary plot averages GHC 4,918 (USD 490), with around 30% of farmers engaged in nonagricultural work. Notably, 62% recognize the benefits of shade, and farmers, on average, adopt nine shade trees per acre. 58% have attended at least one climate-smart agricultural training session, indicating substantial exposure to sustainable practices.

4.4 Balance test

We assess the balance between the four treatment groups of interest and the control group based on various farmer-level baseline characteristics in Appendix Table B.1. Among the four bilateral group pairings, we fail to reject orthogonality for 23 farmer-level covariates at conventional significance levels exploiting an F-test of joint significance. We find significance at the 10% level for two covariates—whether the farmer has high school or more education and whether farming is their main income—but only in one or two bilateral group pairings. Since some analyses of post-lab outcomes were restricted to the Sefwi sample because of data availability, Appendix Table B.2 reports the balance test results across all treatment arms for the Sefwi group only. We include these imbalanced covariates in the regression analyses to mitigate the potential selection bias from these imbalanced factors.

The attrition rate for the lab-session survey in the two regions is 1.2% for farmers. Although the $Input$ group shows a slightly higher attrition rate, the coefficient is 0.007 and statistically significant at the 10% level, suggesting limited concern. Moreover, in the Sefwi sample, the cumulative attrition rate over three follow-up rounds (including the lab-session survey) is 3%, with no treatment arm showing increased attrition relative to the control group (Appendix Table B.3).

4.5 Empirical specification

We estimate the treatment effects of subsidies and information on game-level and farmer-level outcomes during and after the lab, using the following specifications based on five treatment arms, respectively:

$$\text{(Game level)} \quad Y_{ij,s} = \beta_0 + \sum_{k\in\{0,1\}} (\beta_1^k Input_i^{Info=k} + \beta_2^k Output_i^{Info=k}) + \delta L_{ij} + \gamma X_i + \mu_s + \epsilon_{ij,s} \tag{1a}$$

$$\text{(Farmer level)} \quad Y_{i,s} = \beta_0 + \sum_{k\in\{0,1\}} (\beta_1^k Input_i^{Info=k} + \beta_2^k Output_i^{Info=k}) + \gamma X_i + \mu_s + \epsilon_{i,s} \tag{1b}$$

where $Y_{i(j),s}$ represent the outcome variables for farmer i within strata s and (if applicable) game j. These include game decisions such as shade tree planting and real-life outcomes such as GGP tree requests after the lab game. $Input_i^{Info=k}$ and $Output_i^{Info=k}$ are binary variables indicating assignment to the $Input$ and $Output$ subsidy groups based on the information intervention status $Info = k$. The vector X_i comprises farmer-level baseline controls, including any imbalanced covariates identified previously, and additional covariates, selected from 36 potential variables applying the post-double-selection LASSO (PDSLASSO) procedure as proposed by Belloni et al. (2014) and implemented by Ahrens et al. (2019). These selected additional variables may vary with each outcome variable.

L_{ij}, considered only in the game-level analysis, are plot-level land characteristics and farming practices that may influence farmer i's decisions in game j. They include soil type, distance to water sources, and activities such as weeding, spraying, pruning, and fertilizer use. μ_s account for strata fixed effects, while $\epsilon_{i(j),s}$ denotes the error term, with standard errors clustered at the farmer-level. Apart from the main coefficients of interest (β_1^τ and β_2^τ), the differences, $\beta_1^1 - \beta_1^0$ and $\beta_2^1 - \beta_2^0$, capture the impact of information conditional on the *Input* and *Output* subsidies, respectively. We use an F-test for statistical significance of these effects.

To directly examine differential impacts of information and mechanisms across the two subsidy schemes, we further estimate the following equations using the four treatment arms (excluding the control group):

$$\text{(Game level)} \quad Y_{ij,s} = \beta_0 + \beta_1 Output_i + \beta_2 Info_i + \beta_3 Output_i \times Info_i + \delta L_{ij} + \gamma X_i + \mu_s + \epsilon_{ij,s} \quad \text{(2a)}$$

$$\text{(Farmer level)} \quad Y_{i,s} = \beta_0 + \beta_1 Output_i + \beta_2 Info_i + \beta_3 Output_i \times Info_i + \gamma X_i + \mu_s + \epsilon_{i,s} \quad \text{(2b)}$$

where $Y_{i(j),s}$ represent the outcome variables including game decisions, GGP tree requests, and postgame beliefs. Here, $Output_i$ and $Info_i$ are dummy variables indicating assignments to the *Output* subsidy intervention and the *Info* intervention, respectively. With the input-subsidy-only arm as the reference group, β_1 captures the differential impact of the *Output* subsidy relative to the *Input* group, while β_2 represents the impact of information within the *Input* group. Importantly, β_3, the coefficient of the interaction term, represents the differential impact of information when combined with the *Output* subsidy, relative to the *Input* group.

5 Main results

5.1 Impact of subsidies on forest tree planting in the lab

We first evaluate the impact of the two subsidy-only interventions on the primary environmental goal, the number of forest trees planted, in the lab game. Without any information to change farmers' prior beliefs, both subsidies increase the number of forest trees planted, but the increase under the *Output* subsidy is slightly lower (Table 2 and Figure 5a). Farmers in the control group chose to plant 10 trees per acre in the game, consistent with their real-world practices. Farmers in the *Input* subsidy group planted 8.3 more trees per acre (an 82% rise) compared with the control group. Those in the *Output* subsidy group planted 7.6 more trees per acre (a 75% rise) compared with the control.

Table 2: Treatment effects of subsidies on forest trees in the lab

	Forest trees		
	(1) Num. trees	(2) High shade (18+)	(3) Ultra-high shade (25+)
Input	8.29***	0.55***	0.12***
	(0.26)	(0.02)	(0.02)
Output	7.56***	0.53***	0.08***
	(0.25)	(0.02)	(0.01)
Observations	2292	2292	2292
Control mean	10.17	0.05	0.01
P-val: Input = Output	0.01	0.34	0.05

Notes: This table presents the treatment effects on forest shade tree planting decisions on a one-acre cocoa plot in the lab game, based on equation 1a. The regressions are at the game level. Sample includes three treatment groups: control, *Input* subsidy, and *Output* subsidy groups. Regressions control for prespecified land characteristics (e.g., soil type, distance to water source) and farming practices (e.g., rounds of weeding, spraying, pruning, and fertilizer type), strata fixed effects, imbalanced baseline controls, and PDSLASSO-selected baseline control variables. Standard errors in parentheses are clustered at the farmer level. *Num. trees* is the number of forest trees planted on a given one-acre cocoa plot (column (1)). *High shade (18+)* equals 1 if planting at least 18 forest trees in the game, indicating adoption of the High shade level according to the shade criteria (see Table 1) (column (2)); *Ultra-high shade (25+)* equals 1 if planting at least 25 forest trees (column (3)). Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Since the environmental and ecological benefits of forest trees might not be linearly increasing in the number of trees, we evaluate treatment effects on an alternative measure of environmental benefits—whether the density of forest trees reaches a relatively high threshold. We find consistent evidence, with a larger impact under the input subsidy than the output subsidy on the adoption of at least 25 forest trees (Table 2, column (3)). According to the shade levels defined in the subsidy schedule (Table 1), the result suggests that farmers in the *Input* subsidy group are more likely (4 percentage points, or 50% higher than the *Output* subsidy group) to adopt Ultra-high shade (that is, 25+ trees). However, we do not find a significant difference between the *Input* and *Output* groups in the likelihood of reaching the 18-tree threshold for High shade; both subsidies increase farmers' adoption of High shade by over 50 percentage points (Table 2, column (2)).

We also conduct robustness checks and present consistent findings by restricting the sample to either the uniform land game (Table B.4, Panel A) or the individual land game (Table B.4, Panel B) with personalized land characteristics and farming practices across farmers.

5.2 Impact of information nudging combined with subsidy

When these two subsidies are introduced along with a narrative-based information intervention, the information nudging further increases forest tree planting under both subsidies. However, information under the output subsidy has a more pronounced effect, closing the response gap between the two subsidy-only treatment groups (Table 3). Specifically, compared to the corresponding subsidy-only treatment groups, information nudging increases forest tree planting by 1.4 trees per acre under the input subsidy and 2.4 trees per acre under the output subsidy (Table 3, column (1)).

The statistically significant coefficient of the interaction term (*Output* $\times$ *Info*) confirms the larger impact of information nudging when combined with the output subsidy, effectively closing the gap of 0.8 trees between the two subsidy-only treatment groups. Similarly, the gap in adopting at least 25 shade trees (*Ultra-high shade*) is also eliminated by the information (Table 3, column (3)). When examining the adoption of High shade (18+), we find information nudging has a positive impact of similar magnitude under the two subsidies (Table 3, column (2)). Appendix Table B.6 presents robust results when restricting the analysis to either the uniform land game sample (Panel A) or the individual land game sample (Panel B).

Table 3: Treatment effects of information with subsidies on forest trees in the lab

	Forest trees		
	(1) Num. trees	(2) High shade (18+)	(3) Ultra-high shade (25+)
Info	1.43***	0.16***	0.12***
	(0.30)	(0.03)	(0.02)
Output	-0.79***	-0.03	-0.04**
	(0.28)	(0.03)	(0.02)
Output x Info	1.02**	0.05	0.06**
	(0.41)	(0.04)	(0.03)
Observations	3044	3044	3044
Mean (Input)	18.60	0.62	0.13
Mean (Control)	10.17	0.05	0.01
P-val: Input + Info = Output + Info	0.45	0.46	0.33

Notes: This table presents the treatment effects of information given two subsidies using the *Input* subsidy only as a reference group, based on equation 2. The regressions are at the game level. Sample includes four treatment groups: *Input*, *Input+Info*, *Output*, and *Output+Info*. Regressions control for prespecified land characteristics (e.g., soil type, distance to water source) and farming practices (e.g., rounds of weeding, spraying, pruning, and fertilizer type), strata fixed effects, imbalanced baseline controls, and PDSLASSO-selected baseline control variables. Standard errors in parentheses are clustered at the farmer level. *Num. trees* is the number of forest trees planted on a given one-acre cocoa plot (column (1)). *High shade (18+)* equals 1 if planting at least 18 forest trees in the game, indicating adoption of the High shade level according to the shade criteria (see Table 1) (column (2)); *Ultra-high shade (25+)* equals 1 if planting at least 25 forest trees (column (3)). Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We compare all four treatment arms to the control in Figure 5.[22] The results consistently show that information has a larger impact when combined with the output subsidy. With the information intervention, both subsidies increase forest trees per acre by 10 trees compared to the control group.

5.3 Validation outside the lab

Can information nudging and incentivized subsidies for shade in the lab game translate into farmers' responses in the real world? To answer this question and validate the lab-game results, we examine the lab treatment impacts on farmers' requests for forest tree seedlings in the GGP. The GGP is a nationwide afforestation/reforestation initiative that was launched in 2021 and has since been held every June by the government to restore the Ghana's degraded

[22] Coefficient estimates in Tables 2 and 3 and Figure 5 are consistent but slightly different because of the use of different reference groups in regressions.

a. *Input* vs. *Output*, no information **b.** *Input* vs. *Output*, with information

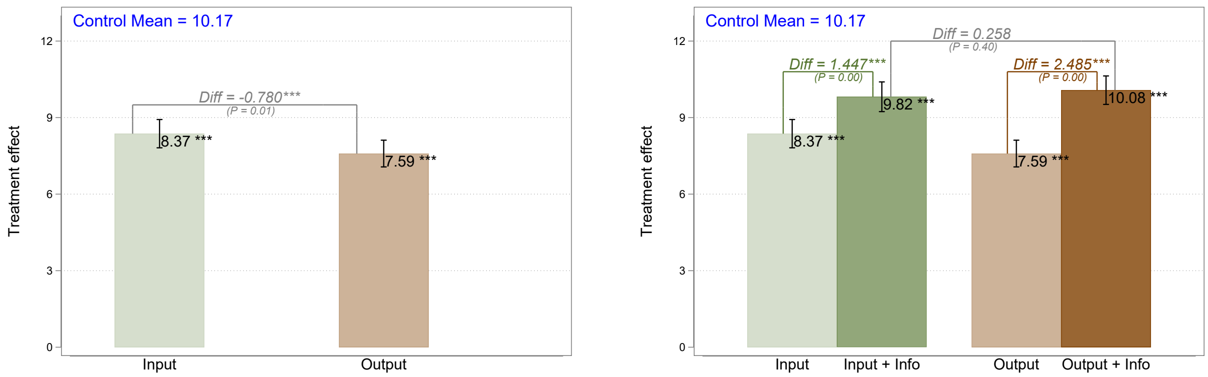


Figure 5: Treatment effects of subsidies and information on forest trees in the lab

Notes: This table presents the treatment effects on number of forest trees planted on a one-acre cocoa plot in the lab game, based on equation 1a. The regressions are at the game level. Sample includes all five treatment groups. Regressions control for prespecified land characteristics (e.g., soil type, distance to water source) and farming practices (e.g., rounds of weeding, spraying, pruning, and fertilizer type), strata fixed effects, imbalanced baseline controls, and PDSLASSO-selected baseline control variables. Standard errors are clustered at the farmer level. Each bar represents the treatment effect magnitude with respect to the control mean: input-based treatments (*Input*; *Input+Info*) are in green, and output-based treatments (*Output*; *Output+Info*) are in brown, with darker shades indicating information treatments. The error bars indicate 95% confidence intervals. Magnitudes and p-values for group differences between each pair are reported. The regression results are also reported in Appendix Table B.5 (column (1)). Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

landscapes. The government encourages everyone to participate in this program and obtain tree seedlings from their local Forest Services Division of the Forestry Commission for free. However, as transportation costs are borne by individuals and the information campaign rarely reaches rural neighborhoods, most of our sampled farmers never participated. As the free tree seedlings are equivalent to a subsidy linearly increasing in the number of trees, the GGP can be viewed as an input subsidy.

As part of the validation process, we collected information about each farmer's request for forest tree seedlings in the GGP at three stages: a *lab exit survey* right after the lab game, a *phone survey* three months after the lab, and a *tree-seedling distribution* following the phone survey. The last two stages were conducted only in the Sefwi district due to logistic and budget constraints.[23] During the phone survey, farmers who expressed interest in requesting forest tree seedlings in the lab exit survey were asked to confirm or update their initial GGP sign-up

[23] All forest tree seedlings were prepared and generously supported by the Forestry Commission of Ghana.

decisions. They were informed that the requested seedlings would be distributed at their community assembly according to their sign-up records.[24] During the seedling distribution, farmers were informed of the time and location two days in advance. Although encouraged to attend, farmers could choose not to or could send a representative to pick up the seedlings on their behalf. We recorded attendance by self or representative, number of seedlings picked up, and transportation cost in terms of time and money.[25] Due to equity concerns and limited seedling inventory in the local nursery, each farmer could receive a maximum of 25 seedlings.

In the full sample, farmers' responses to the lab exit survey questions about the GGP are very consistent with the in-lab outcomes of forest shade tree planting (Figure 6). Figure 6a indicates that without any information, participants in the *Input* subsidy group in the lab game requested 1.95 more forest tree seedlings (a 12.3% increase, compared to the control mean of 15.9) during the GGP, while the magnitude is 1.13 (42% smaller) for the *Output* group. This discrepancy aligns with the lab-game outcome of forest shade tree planting and is economically significant, though we are not powered to reject the null of equal impact size (p-value = 0.12). Figure 6b corroborates the finding that information nudging is more effective when combined with the output subsidy. While we document a positive impact of information nudging on farmers under both subsidy groups, information nudging coupled with the output subsidy results in an additional 1.48 tree requests, which is larger than the 0.93 more trees under the input subsidy. As a result, when coupled with the information intervention, the response gap in seedling requests under the GGP between the two subsidy treatments is reduced from 0.82 (p-value = 0.12) without information nudging to 0.27 (p-value = 0.80) with nudging.

Zooming in on the sample from Sefwi, we first show internal validity in the lab exit survey by demonstrating consistency with the full sample, then leverage the tree-seedling distribution to discuss the implications outside the lab. Column (2) of Table 4 shows that the relative magnitudes and ordering of the treatment effects remain consistent with the full sample in column

[24] The majority (79%) adhered to their initial decisions from the *lab exit survey*, while 7% decided not to participate, because, for example, fires destroyed their farms or they already received tree seedlings from other sources after the lab game. The high consistency with original decisions suggests that the unincentivized lab exit survey could already provide fairly credible results.

[25] As the distribution happens at the community assembly, most farmers were able to attend on foot without incurring additional transportation costs.

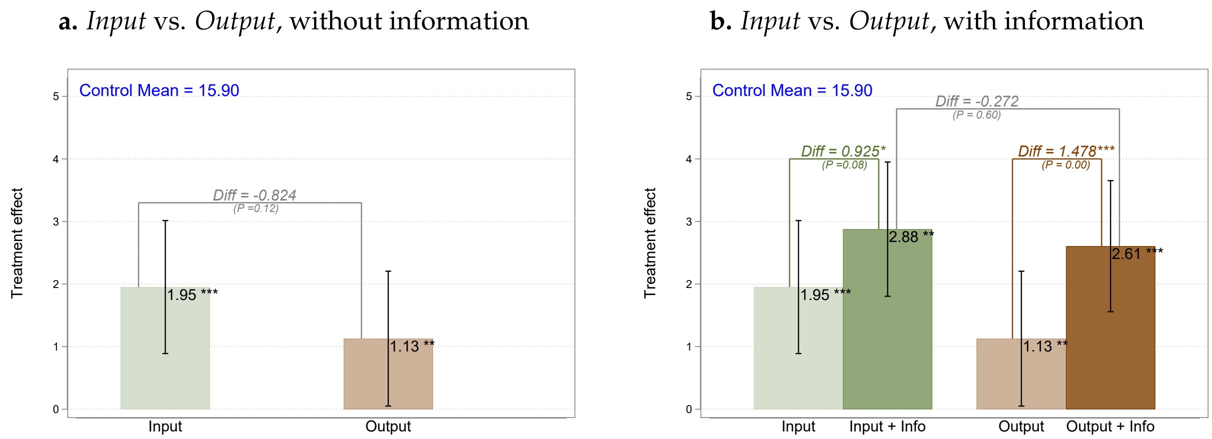


Figure 6: Green Ghana Program sign-ups (lab exit survey)

Notes: This figure presents the treatment effects on the number of forest tree seedlings that farmers signed up for and planned to plant on their cocoa farms during the Green Ghana Program (GGP). Each respondent's GGP sign-up intentions were collected in the lab exit survey during the lab session. Regressions control for strata fixed effects, imbalanced baseline controls, and PDSLASSO-selected baseline control variables. Standard errors are clustered at the farmer level. Each bar represents the treatment effect magnitude with respect to the control mean: input-based treatments (*Input*; *Input+Info*) are in green, and output-based treatments (*Output*; *Output+Info*) are in brown, with darker shades indicating information treatments. The error bars indicate 95% confidence intervals. Magnitudes and p-values for group differences between each pair are reported. The regression result is also reported in Table 4 (column (1)). Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(1), despite less precision, underscoring the robustness of the findings. However, we are not powered to reject the null that the effects of the subsidy-with-information treatment are different from the subsidy-only ones. On the consistency between sign-up and pickup, Figure 7 compares the treatment effects of subsidies and information on the number of forest trees requested or obtained during the lab exit survey, phone survey, and seedling distribution for the Sefwi sample. Despite a lengthy time span of three months and the fully voluntary nature of the sign-up process, we find consistent ordering and magnitudes of treatment effects as in the lab.[26] These consistent patterns demonstrate the lasting influence of within-lab information nudging on real-life decisions.

Treatment effects of in-lab subsidies and information on out-of-lab outcomes demonstrate similar patterns to in-lab outcomes for both sign-up (Table 4, column (3)) and pickup (columns (4)–(6)). Column (3) shows similar treatment effect magnitudes between incentivized sign-up with later pickup responses. Column (4) shows that farmers assigned to the *Input* subsidy

[26] Corresponding coefficients are presented in Table 4 (columns (1)–(4)).

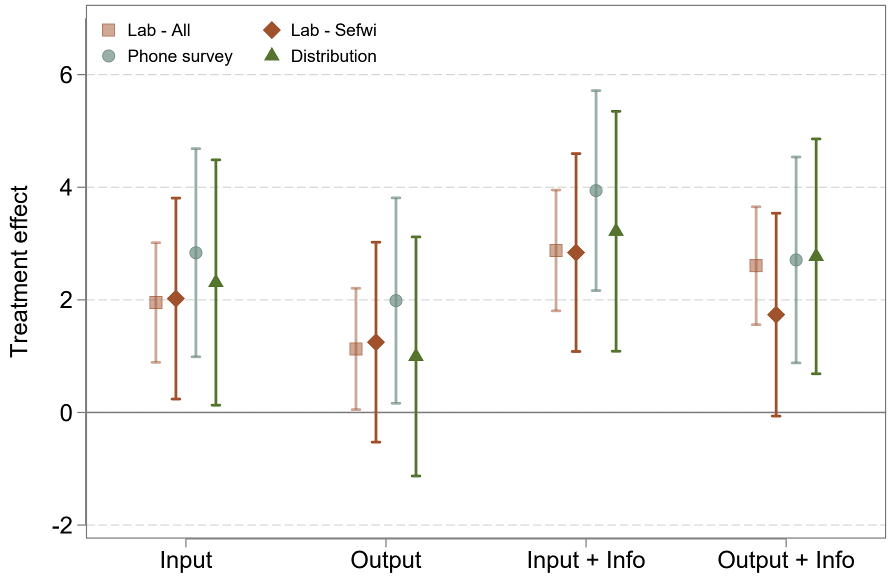


Figure 7: Treatment effects of subsidies and information on tree seedlings requested and obtained

Notes: This figure presents the treatment effects on the number of forest tree seedlings that farmers indicated they would plant on their cocoa farms for the Green Ghana Program, measured in lab exit survey, post-lab phone survey, and actual distribution. The responses in lab exit surveys and phone surveys are winsorized at 25 per farmer. The number of trees distributed is capped at 25 per farmer. Regressions control for strata fixed effects, imbalanced baseline controls, and PDSLASSO-selected baseline control variables. Standard errors are clustered at the farmer level. 95% confidence intervals are shown. The regression results are also reported in Table 4 (columns (1)–(4)). Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

group in the lab obtained 2.34 more seedlings than the control group (a 15.5% increase), while no significant impact was observed under the *Output* group. When adding information to the subsidies, farmers with an information nudge obtained 1.7 more seedlings compared to those in the output-only group (p-value = 0.07). This combination narrowed the gap between the two subsidy groups from 1.3 (p-value = 0.21) to 0.5 (p-value = 0.66) trees per farmer. On the alternative measure—whether obtained the maximum number of 25 seedlings, information added a significant positive effect only when paired with the *Output* subsidy; otherwise neither the *Input* nor *Output* subsidy alone had a statistically significant impact.

Last, column (6) of Table 4 shows the extensive margin—whether participants showed up for tree seedlings on distribution day—which is already high (78%) in the control group. This rate is not affected by the subsidy-only treatments but is further boosted by information nudging in the *Output* group. We can reject the null that the output subsidy with information nudging is not different from the output-only group at the 10% significance level.

Table 4: Decisions on Green Ghana Program (GGP)

	Lab Exit Survey		Phone survey	Distribution Day		
	(1) Tree request	(2) Tree request	(3) Tree request	(4) Actual pickup	(5) $\mathbb{1}_{Trees \geq 25}$	(6) Show-up
Input	1.95***	2.02**	2.84***	2.31**	0.06	0.07
	(0.54)	(0.91)	(0.94)	(1.11)	(0.06)	(0.05)
Output	1.13**	1.25	1.99**	0.99	-0.01	0.02
	(0.55)	(0.91)	(0.93)	(1.08)	(0.06)	(0.05)
Input + Info	2.88***	2.84***	3.94***	3.22***	0.15**	0.07
	(0.55)	(0.90)	(0.91)	(1.09)	(0.06)	(0.05)
Output + Info	2.61***	1.74*	2.71***	2.77***	0.12**	0.09**
	(0.53)	(0.92)	(0.93)	(1.06)	(0.06)	(0.04)
Observations	1905	601	601	601	601	601
Control Mean	15.90	17.18	16.63	15.21	0.34	0.78
P-val: Input = Output	0.12	0.35	0.31	0.21	0.23	0.29
P-val: Input = Input + Info	0.08	0.31	0.18	0.39	0.12	1.00
P-val: Output = Output + Info	0.00	0.56	0.39	0.07	0.02	0.10
P-val: Input + Info = Output + Info	0.60	0.18	0.13	0.66	0.60	0.63
Sample	All	Sefwi	Sefwi	Sefwi	Sefwi	Sefwi

Notes: This table presents the treatment effects on farmers' requests for forest tree seedlings during the Green Ghana Program (GGP), with column (1) using the full sample from both regions and columns (2)–(6) using the sample from Sefwi Bekwai only. Columns (1)–(2) show impacts on the number of forest tree seedlings requested for cocoa farms during the lab exit survey. Column (3) reports farmers' requests for forest tree seedlings in the phone survey conducted three months after the lab experiment, in which farmers were allowed to adjust their responses from the lab and were informed of an upcoming tree seedlings distribution event at their community assembly place. Columns (4)–(6) report the actual number of tree seedlings picked up, whether the number is at the cap of 25, and whether the farmer showed up on the distribution day. Regressions control for strata fixed effects, imbalanced baseline controls, and PDSLASSO-selected baseline control variables. Standard errors in parentheses are clustered at the farmer level. "P-val," below each panel, reports the p-value for the group t-test for each treatment pair (listed in parentheses). Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6 Theoretical framework

Both lab outcomes and post-lab validation demonstrate a larger impact of information nudging when combined with the output than the input subsidy. To explore the underlying mechanism, we develop a theoretical framework to rationalize farmers' optimal decisions regarding shade trees when maximizing expected profits under the two subsidy schemes. We account for individual beliefs along two dimensions: one concerning climate risks, and the other related to shade benefits. The model aims at both unpacking the theoretical rationales for different responses driven by the same information under the two subsidy schemes and providing guidance for empirical tests of the mechanisms and heterogeneity analysis.

6.1 Model setup

Beliefs. Each farmer's belief set Θ encompasses a broad range of subjective beliefs, including perceptions of how climate risks and adaptation tools enter into their production function. Since we are focusing on shade trees as a particular adaptation tool taken against abnormally low or variable rainfall, we specifically model beliefs about rainfall patterns and shade benefits.[27] Beliefs about shade benefits are captured by the marginal returns of shade trees to production under varying rainfall conditions. Together, these beliefs about climate risks and shade benefits shape the structure of the production function.

Production function. We model a univariate output production function as follows:

$$Y(T;\theta,r) = y + \theta T - f(T,r) \tag{3}$$

where the number of shade trees (T) and rainfall (r) jointly determine the yield (Y) of cocoa beans. The yield benchmark, y, reflects the yield level determined by other non-tree inputs such as farming practices (for example, weeding, irrigation, fertilizer use). Shade trees influence production through two channels: a positive constant return to shade independent of rainfall, represented by θ; and an interactive effect of rainfall and shade trees, captured by the loss function $f(T,r)$.

In fact, rainfall and shade trees have interactive effects on cocoa production, which are reflected in the loss function $f(T,r)$. First, cocoa production requires certain amount of irrigation, which is made difficult by drought. Therefore, the loss function is decreasing in rainfall: $\frac{\partial f(T,r)}{\partial r} < 0$. Second, shade trees are more beneficial during drought than under normal rainfall. Therefore, we expect increasing marginal returns to shade trees when rainfall is low: $\frac{\partial^2 f(T,r)}{\partial T \partial r} > 0$.

[27] Deryugina and Hsiang (2017) note that the marginal effects of climate change can be identified using local weather variations. Therefore, we use rainfall patterns as a proxy for climate change.

Two types of subsidy schemes. We now model the *Input* subsidy scheme $g^I(T)$ and *Output* subsidy scheme $g^O(T,Y)$ over a continuous measure of T for tractability:

$$\textit{Input}: \qquad g^I(T) = \rho T, \ \rho > 0 \tag{4a}$$

$$\textit{Output}: \quad g^O(T,Y) = (\tau T) \times pY, \ \tau > 0 \tag{4b}$$

The *Input* subsidy $g^I(T)$ is a direct cash transfer that is linear in shade level, where ρ represents the cash subsidy per tree. In contrast, the *Output* subsidy is a price premium that is linear in shade level for cocoa beans produced by shaded farms, where τ represent the price premium per tree for one bag of cocoa beans. Therefore, the cash value of the *Output* subsidy, $g^O(T,Y)$, is the product of the shade-specific price premium τT, the market price p, and the cocoa bean yield Y. We adopt this linear form for simplicity, as it conveys the intuition that if farmers plant shade trees scattered around cocoa farms, the number of shade trees serves as a proxy for the proportion of shaded cocoa and the price premium is paid only for shaded cocoa.

Farmer's optimization problem. Each farmer makes their input decision regarding shade trees ex ante by maximizing expected profits before the rainfall level is realized:

$$\begin{aligned}\max_T \mathbb{E}[\pi(T)] &\equiv \int \left[pY(T;\theta,r) - C(T) + g^j(\cdot)\right] \phi(r)dr, \ \ j \in \{I, O\} \\ &= \begin{cases} p\mathbb{E}(Y) + \rho T - C(T), & \text{if } \textit{Input} \\ p(1+\tau T)\mathbb{E}(Y) - C(T), & \text{if } \textit{Output} \end{cases}\end{aligned} \tag{5}$$

where $C(T)$ denotes the cost function of shade trees, which is twice continuously differentiable and convex: $C(T) \geq 0$, $\frac{\partial C(T)}{\partial T} > 0$, and $\frac{\partial^2 C(T)}{\partial T^2} \geq 0$. This reflects the conventional view of increasing marginal costs for production inputs.

Before solving the optimization, we discuss the intuition for different responses to two subsidy schemes under information nudging. As the subsidy level increases, marginal returns to shade constantly increase in ρ under the input subsidy, whereas the rate varies with τ under the output subsidy, depending on the expected yield:

$$\textit{Input:}\quad \frac{\partial^2 \mathbb{E}(\pi)}{\partial \rho \partial T} = 1 \tag{6a}$$

$$\textit{Output:}\quad \frac{\partial^2 \mathbb{E}(\pi)}{\partial \tau \partial T} = p\left[\mathbb{E}(Y) + T\frac{\partial \mathbb{E}(Y)}{\partial T}\right] \tag{6b}$$

As a result, if information nudging updates beliefs about rainfall or shade benefits, expected yield $\mathbb{E}(Y)$ changes. This change would affect the rate at which marginal returns to planting shade trees evolve as increasing subsidy levels, but only under the *Output* subsidy.

6.2 A simple specification

In this section, we solve a more specific model to formally test the predictions.

To fix ideas, we adopt the following parametric specifications for the loss function $f(T, r)$, the rainfall distribution $\phi(r)$, and the cost function $C(T)$ for analytical convenience. We solve the model for the optimal decisions regarding shade trees and conduct comparative statics to explore the potential for a larger impact of information under the *Output* subsidy.

The loss function takes the following fractional form:

$$f(T, r) = z\frac{T^m - T}{r}, z > 0 \tag{7}$$

where T^m denotes a sufficiently high tree level beyond which rainfall has no impact, assuming that $T \in [0, T^m]$. The parameter $z > 0$, representing sensitivity of returns to deviations under varying rainfall, serves two purposes. First, a larger z implies a greater marginal shade benefit: $-\frac{\partial f(T,r)}{\partial T} = \frac{z}{r} > 0$. Second, it suggests a greater drought-related loss given rainfall, as indicated by $\frac{-zT^m}{r}$.[28]

In addition, we assume rainfall r is stochastic: a low state of $(\mu - \sigma)$ with probability k, and a high state of $(\mu + \sigma)$ with probability $(1 - k)$, where $\mu > \sigma > 0$. For simplicity, we further

[28]Correspondingly, in the belief module of the survey, we use two relevant questions to measure z: confidence in shade benefits (0–10 scale) and perceptions of yield changes due to prolonged drought (see Appendix Table B.10).

assume $k = \frac{1}{2}$.

$$\phi(r) : r \sim k\mathbb{1}_{\{\mu-\sigma\}} \oplus (1-k)\mathbb{1}_{\{\mu+\sigma\}}, \text{where } k = \frac{1}{2}, \mu > \sigma > 0 \tag{8}$$

Therefore, a farmer's belief set Θ can be defined by the following four parameters:

$$\Theta \equiv \{\theta, z, \mu, \sigma\} \tag{9}$$

where θ and z reflect shade benefits, while μ and σ reflect climate risks.

We then assume a convex cost function in quadratic form:

$$C(T) = c_0 + c_1 T + c_2 T^2, \text{with } c_2 > 0,\ c_0 = 0 \tag{10}$$

Given the above specifications, the optimal number of shade trees under two subsidy schemes, denoted as $T_j^*,\ j \in \{I, O\}$, can be determined by maximizing expected profit:

$$\max_T \mathbb{E}[\pi(T)] \implies$$

$$\textit{Input: } T_I^* = \frac{(\theta p - c_1)(\mu^2-\sigma^2) + pz\mu}{2c(\mu^2-\sigma^2)} + \frac{\rho}{2c} \tag{11a}$$

$$\textit{Output: } T_O^* = \frac{(\theta p - c_1)(\mu^2-\sigma^2) + pz\mu}{2c(\mu^2-\sigma^2) + 2\tau pA} + \frac{\tau}{2c}\frac{p[y(\mu^2-\sigma^2) - z\mu T^m]}{(\mu^2-\sigma^2) + \tau pA/c} \tag{11b}$$

where $A = z\mu - \theta(\mu^2 - \sigma^2)$.

Role of information. We then examine the impact of information under the two subsidy schemes. As outlined in Section 3.2, the information provided emphasized greater shade benefits, particularly under drought conditions, along with increasing climate risks, reflected in irregular rainfall patterns and higher drought losses. Accordingly, the information intervention implies larger shade benefits (reflected by $\uparrow \theta$ or $\uparrow z$) or greater drought losses (reflected by $\uparrow z$ or $\uparrow \sigma$).

We formalize the impacts of information by exploring the marginal responses to shifts in belief components as subsidy levels increase, which are presented in two propositions.

Proposition 1 *Under the input subsidy, the impact of information is independent of the subsidy level ρ.*

Proposition 2 *Under the output subsidy, the impact of information is undetermined, and may be positive when the subsidy level τ is raised.*

Proof. See Appendix C for the full derivative. ■

Proposition 1 states that the impact of information under the *Input* subsidy does not depend on the subsidy level and stays constant. In contrast, Proposition 2 states that the impact of information under the *Output* subsidy is reliant on the subsidy level. Specifically, when $\frac{\partial^2 T_O^*}{\partial z \partial \tau}$ > 0 or $\frac{\partial^2 T_O^*}{\partial \sigma \partial \tau} > 0$, the impact of information can complement the impact of an increase in the *Output* subsidy τ.

We now turn to our experimental data to empirically test the mechanisms by identifying which belief components are shifted by the information and conduct the heterogeneity analysis by prior beliefs, following the introduction of measures for different belief components in the survey (Appendix Table B.10 and Figure B.5). Finally, we calibrate key belief parameters using the method of minimizing the sum of squares, followed by counterfactual analysis.

7 Empirical mechanisms

Guided by the theoretical model, this section explores the mechanisms by first presenting empirical evidence from the experimental data regarding which components of beliefs are shifted by information nudging. We then examine heterogeneity across the two subsidy schemes based on prior beliefs. Last, we calibrate the model to match key patterns observed in the experimental data and conduct counterfactual analysis to quantify the impacts of information when increasing subsidy levels under both schemes.

7.1 Which parts of beliefs are shifted by information?

What drives the impact of information when combined with subsidies? We investigate how information nudging shifts farmers' beliefs about climate risks and the benefits of shade (Table 5). To align with the model's definition of z, the sensitivity of shade returns, we measure

Positive update as an increase in z, reflected either by increased recognition of shade trees' role in stabilizing yield during drought or by a correct understanding of the magnitude and direction of drought's impact on cocoa production after the lab game.[29] Information nudging increases the likelihood of farmers' updating their beliefs in the correct direction by 7 percentage points (a 9.2% increase compared to the input-only group mean) (Table 5, column (1)). This is consistent with the fact that information on both drought-based loss and shade tree benefits was provided in the information treatment. However, we find no evidence of belief updates regarding a less predictable future rainfall pattern after the information (Table 5, column (2)).

Table 5: Treatment effects of information on belief updating: shade benefit or drought loss

	Shade benefit	Climate risk	Production function	
	(1)	(2)	(3)	(4)
	Positive update	Less predictable	Optimal shade	Opt. shade increase
Info	0.07**	-0.01	1.03*	0.08*
	(0.03)	(0.25)	(0.57)	(0.04)
Output	0.02	0.02	0.18	0.01
	(0.03)	(0.24)	(0.55)	(0.04)
Info x Output	-0.01	-0.00	0.15	-0.02
	(0.04)	(0.34)	(0.77)	(0.06)
Observations	1522	495	495	495
Input Mean	0.76	8.25	16.48	0.20
Baseline belief	Yes	Yes	Yes	Yes
P-val: Output = Output + Info	0.02	0.95	0.03	0.15
Sample	All	Sefwi	Sefwi	Sefwi

Notes: This table presents the information treatment effects on farmers' beliefs about shade tree benefits and drought impact on cocoa production. The regressions are at the individual level. *Positive update* equals 1 if farmers either increased their confidence in shade trees' role in stabilizing yield, or believed that extended drought could lead to a 0%–25% loss in cocoa production after the game. *Less predicable* represents the posterior recognition of less predictable future rainfall pattern after information nudging (column (2)). Optimal shade is farmers' optimal shade level (number of forest trees per acre) implied by their self-reported production function, under harsh weather (column (3)). *Opt. shade increase* equals one if the posterior optimal shade level increases compared to the prior level under harsh weather (column (4)). All posterior beliefs are measured during the lab exit survey. Regressions include all treatment arms except the control group. Regressions control for strata fixed effects, imbalanced baseline controls, and PDSLASSO-selected baseline control variables. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We measure each farmer's optimal shade level under normal and harsh weather conditions by the number of forest trees per acre that achieves the highest yield, jointly determined

[29] Appendix Table B.10 provides a list of relevant survey questions in the belief module, corresponding to each belief component captured in the model. Appendix Figure B.5 presents the distribution of selected belief measures at baseline, prior to information nudging.

by different belief components.[30] This is derived from their self-reported expected cocoa production function on their main plot, based on shade levels varying from 0 to 25 forest trees per acre, collected in both the baseline survey and lab exit survey (Appendix Figure B.6a).[31] We find that farmers under the information intervention are more likely to increase their optimal shade level, resulting in a higher posterior optimal shade under harsh weather compared to the subsidy-only treatment groups (Table 5, columns (3) and (4)). On average, the information intervention results in a higher posterior optimal shade level by 1 tree per acre, a 6% increase relative to the posterior mean of 16.48 trees per acre in the *Input* group (Table 5, column (3)). Similarly, farmers in the information treatment are 8 percentage points more likely to increase their optimal shade level after the game, a 40% increase compared to the *Input* group (posterior mean of 0.2) (Table 5, column (4)). Appendix Figure B.7 (Panels (a) and (c)) presents the distribution of posterior optimal shade levels relative to prior beliefs under harsh weather, comparing the subsidy-with-information and subsidy-only treatment groups. We see consistent evidence that more probability mass falls under higher optimal shade levels under harsh weather with information nudging. However, there is no significant impact on perceived optimal shade levels under normal weather (Appendix Figure B.7, Panels (b) and (d)).

7.2 Heterogeneity by prior beliefs

We further investigate the heterogeneous treatment effects of subsidies and information on forest trees planted in the lab game by individual beliefs about shade benefits (Table 6, columns (3)–(4)) and future climate risks (Table 6, columns (5)–(8)). Though we find no evidence of shifts in beliefs about climate risks, prior beliefs regarding climate risks (captured by both rainfall level and variability) remain important for ex ante decisions on shade levels.

We first explore the role of prior beliefs about shade benefits, with and without information

[30] It is worth noting that the average prior agreement level among sampled farmers, collected in baseline survey, is sufficiently high (7.9 out of 10) based on the full sample. Therefore, to capture farmers' perceptions of shade benefits more precisely, we included additional questions about farmers' perceived cocoa production under different shade levels on their main plot, specifically for the Sefwi group.

[31] Appendix Figure B.6a shows that the average optimal shade in the baseline survey under both weather conditions is 13.6 forest trees per acre in the control group from Sefwi. We estimate each farmer's optimal shade level separately, applying the same method, and Appendix Figure B.6b presents the distribution of farmers' prior perceived optimal shade levels under normal and harsh weather.

Table 6: Heterogeneous treatment effects of subsidies and information on forest trees in the lab

	Overall		Shade benefit		Climate risk			
	(1) No-info	(2) Info	(3) No-info	(4) Info	(5) No-info	(6) Info	(7) No-info	(8) Info
Output	-0.74***	0.23	-0.26	0.02	-0.39	-0.25	-0.42	-0.72**
	(0.26)	(0.27)	(0.34)	(0.34)	(0.39)	(0.36)	(0.36)	(0.37)
Less agreed on shade			1.10*	-0.24				
			(0.63)	(0.69)				
Output x *Less agreed on shade*			-1.09	0.57				
			(0.67)	(0.66)				
Expect less rain					-0.20	-0.54		
					(0.47)	(0.50)		
Output x *Expect less rain*					-0.84	1.25*		
					(0.65)	(0.72)		
Less predictable							0.27	0.10
							(0.48)	(0.45)
Output x *Less predictable*							-0.36	1.43***
							(0.56)	(0.54)
Observations	1526	1518	1526	1518	1526	1518	486	504
Mean (Input)	18.60	19.98	18.60	19.98	18.60	19.98	18.15	20.07
P-val: Output + Output x $\mathbb{1}_{hetero}$ = 0			0.01	0.26	0.01	0.07	0.03	0.05
Sample	All	All	All	All	All	All	Sefwi	Sefwi

Notes: This table reports the heterogeneous treatment effects of subsidies and information on forest trees, with columns (1)–(6) using the full sample , while columns (7)–(8) restrict the sample to the Sefwi group. The heterogeneity cut is based on farmers' prior beliefs about shade benefits and climate risks (including both rainfall level and variability). *Less agreed on shade* equals 1 if farmers are in the below-median group for recognizing shade benefits in stabilizing yields. *Expect less rain* equals 1 if farmers expect more drought and less rainfall (measured by number of rainy days) in the future compared to the last 10 years. *Less predictable* equals 1 if farmers fully agree that rainfall patterns would be less predictable in the future. Both prior beliefs are measured in the baseline survey. *Non-Info* columns (odd columns) are based on *Input* and *Output* treatment groups, and *Info* columns (even columns) are based on *Input+Info* and *Output+Info* treatment groups. The regressions are at the game level. Regressions control for prespecified land characteristics (e.g., soil type, distance to water source) and farming practices (e.g., rounds of weeding, spraying, pruning, and fertilizer type), strata fixed effects, imbalanced baseline controls, and PDSLASSO-selected baseline control variables. Standard errors in parentheses are clustered at the farmer level. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

nudging (Table 6, columns (3)–(4)). Without information, farmers with below-median recognition of shade benefits at baseline tend to plant 1.09 fewer trees than the reference group within the *Input* group, while no such difference is observed after the information intervention.

We also look into the role of beliefs about climate risks, specifically perceptions of prolonged drought and their impact on output subsidies (Table 6, columns (5)–(6)). *Expect less rain* equals 1 if farmers expect fewer rainy days during the dry season in the future compared to the past decade, and 0 otherwise.[32] We find that the observed difference of 0.74 trees per acre

[32]Forty percent of sampled farmers hold this pessimistic view, balanced across all treatment groups, as shown

between the two subsidy-only groups (Table 6, column (1)) is primarily driven by pessimistic farmers, who expect lower future rainfall. Farmers in the *Output* subsidy group who hold this belief tend to plant 1.2 fewer trees compared to non-pessimistic farmers in the *Input* group (Table 6, column (3)). Since the total subsidy under the output subsidy depends on the amount of cocoa beans harvested, farmers pessimistic about future rainfall anticipate lower subsidy rewards and thus adopt fewer shade trees.

However, when the output policy is offered together with information nudging, we observe a larger positive impact of information intervention compared to the *Input+Info* group, closing the initial response gap (Table 6, column (4)). The output subsidy structure, combined with the evidence that information nudging shifts farmers' beliefs about shade benefits, leads to higher expected subsidy income under the output-based policy.

Another salient way that climate change could affect farming yields is through changing rainfall patterns. We investigate how treatment effects vary by beliefs about rainfall variability (Table 6, columns (7)–(8)). The variable *Less predictable* reflects whether farmers fully agree with the statement that future rainfall patterns would be less predictable. Without information, pessimistic farmers who expect greater rainfall variability plant 0.78 fewer forest trees than those in the *Input* group (Table 6, column (7)). However, when combined with information, this subgroup of farmers in the *Output+Info* group increases their shade adoption more than the *Input+Info* group. In a nutshell, we find more evidence that the information intervention has a more pronounced positive impact on forest trees planted by farmers with more pessimistic beliefs about climate shocks—either lower rainfall level or larger rainfall variability—because of concerns about the shocks' negative effects on cocoa production.

7.3 Model estimation and counterfactuals

Putting together the theoretical structure and empirical evidence, we calibrate the model from Section 6.2 to match key patterns observed in the experimental data, then conduct counterfactual analysis, focusing on the impact of increasing subsidy levels. Table 7 summarizes the model parameters, estimated through the following steps.

in the balance tests in Table B.1. See the relevant survey question in Appendix Table B.10.

Table 7: Summary of model parameters

Parameter	Description	Source	Value
θ	Returns per tree (num. bags)	Calibrated	0.0187
σ	Rainfall variability	Calibrated	63.20
c_2	Convexity of cost function	Calibrated	0.5457
z'	(Post) sensitivity of returns	Calibrated	0.22
z	(Prior) sensitivity of returns	Fixed	0.08
μ	Rainfall average level	Fixed	100
T^m	Sufficiently large shade level where rainfall has no effect	Fixed	40
y	Yield benchmark (num. bags)	Fixed	1.2
ρ	*Input*: subsidy per tree	Data	9
τ	*Output*: price premium per tree	Data	0.0058
$\bar{T}$	Threshold shade level for subsidy payout	Data	7
p	Price per bag of cocoa beans	Data	800
c_1	Cost per tree	Data	5
c_0	Constant term of cost function	Data	0

Notes: This table provides the summary of model parameters.

The first set of parameters are derived directly from the lab experiment design. Specifically, the minimum shade level required to qualify for subsidy benefits ($\bar{T}$), the market price of cocoa beans per bag (p), and the linear cost per tree (c_1) are all taken from the lab-game setting (see details in Table 1). The subsidy levels under the *Input* and *Output* schemes, represented by ρ and τ, respectively, are estimated by applying a continuous linear approximation of the four-tiered menu of subsidies.[33] For the *Input* scheme, $\rho = 9$ implies that a one-acre cocoa plot with 25 forest trees qualifies for a fixed subsidy level of 0.28 bags[34] of cocoa beans. For the *Output* scheme, $\tau = 0.0058$, representing a 0.58% price premium per tree, suggests that a one-acre cocoa plot with 25 forest trees qualifies for a 14.5% price premium.

We additionally fix the values of T^m, y, and μ outside of the estimation process. First, the sufficiently large shade level, T^m, is set to 40 trees per acre, at which point yield is supposed to become independent of rainfall.[35] The yield benchmark, excluding the impact of shade trees, y, is fixed at 1.2 bags, based on farmers' average self-reported expected yield under normal weather with no shade and unchanged non-tree inputs.[36] The average monthly precipitation is

[33] Appendix Figure B.4 justifies the close fit between the four-tier subsidy in the lab (Table 1) and the continuous proxy in equation 4.

[34] Calculation here: (9×25) / 800 = 0.28 bags, with 1 bag = 64 kg of cocoa beans.

[35] We also conduct a sensitivity test by varying T^m to evaluate the robustness of the model.

[36] In principle, farmer-specific perceived yield without shade (y_i) is available, but we use the sample mean for this simplified analysis in the current stage.

normalized to 100, and rainfall variability can be interpreted relative to this baseline.

Finally, the remaining parameters, θ, σ, c_2, and z, are estimated by matching the moments of model-predicted and observed average shade tree adoption across the five treatment arms, minimizing the sum of squared differences. The parameter c_2 captures the increasing marginal costs in the cost function. In theory, belief-relevant parameters θ, σ, and z, which shape the production function, should be estimated separately for the subsidy-with-information and subsidy-only groups. However, we find no evidence that the information intervention shifts farmers' beliefs about climate risk (Table 5, column (2)) or their perceptions of shade benefits, regardless of rainfall (Figure B.7, Panels (b) and (d)).[37] Therefore, we estimate common values of θ and σ for all treatment groups. Since column (1) of Table 5 shows evidence of a positive impact of information on the recognition of shade benefits under drought, reflected in a higher value of z, we set $z = 0.08$ for the subsidy-only groups and estimate z' for the subsidy-with-information groups under the constraint that $z' > 0.08$.

Illustration of model fit. Figure 8 demonstrates the model's satisfactory fit, as the calibrated model patterns align well with the observed patterns. It also shows that increased sensitivity to returns following the information treatment leads to a decline in farmers' expected profits under both subsidy schemes, suggesting that the larger drought losses outweigh the benefits from increased marginal shade returns. Last, the figure highlights the response gap due to information under the two subsidy schemes, illustrating how farmers adjust their shade tree decisions upward from their previous optimal choices (hollow points) along the updated expected profit profile after incorporating the information intervention.

Counterfactual. We conduct a counterfactual analysis by incrementally increasing the subsidy level and quantifying the impact of information on adoption (Figure 9). When the input subsidy is raised by 33.3%, corresponding to an increase in the price premium τ from 0.0058 to 0.0079,[38] we observe a more pronounced effect of information under the output subsidy. As the

[37]Panels (b) and (d) of Figure B.7 show no significant impact of information on perceived optimal shade levels under normal weather, suggesting a common value of θ prior to and after the information treatment.

[38]A premium of 0.79% per tree, or approximately 19.8% for a cocoa plot with 25 forest trees per acre, remains within a reasonable range.

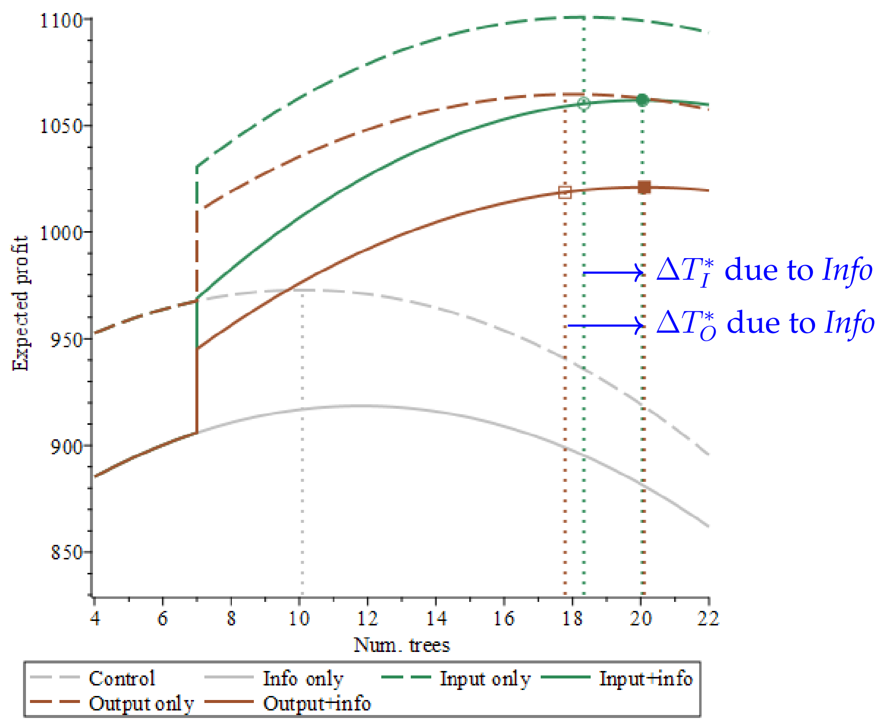


Figure 8: Expected profit function with and without information (lab subsidy)

Notes: This figure illustrates the relationship between farmers' expected profit and the number of shade trees under different subsidy schemes, both with and without information, based on calibrated parameters. Dashed curves represent the scenarios without information, while solid curves indicate the scenarios with information. The vertical dotted lines represent the optimal number of shade trees that maximize expected profit under each scenario. The hollow points show the expected profit given the previous optimized decisions (under the scenarios of subsidy-only interventions) after incorporating the information intervention.

subsidy level increases, the optimized decision under the output subsidy surpasses that under the input subsidy by 6.5%. Therefore, when combined with the information intervention, the output subsidy has the potential to outperform the input subsidy in driving adaptation.

8 Other lab outcomes

8.1 Demand for subsidies

To further examine the lab treatment impacts at the extensive margin—farmers' enrollment in a subsidy program—we investigate how these lab treatments influence their demand for learning about and enrolling in a similar subsidy program in real life.

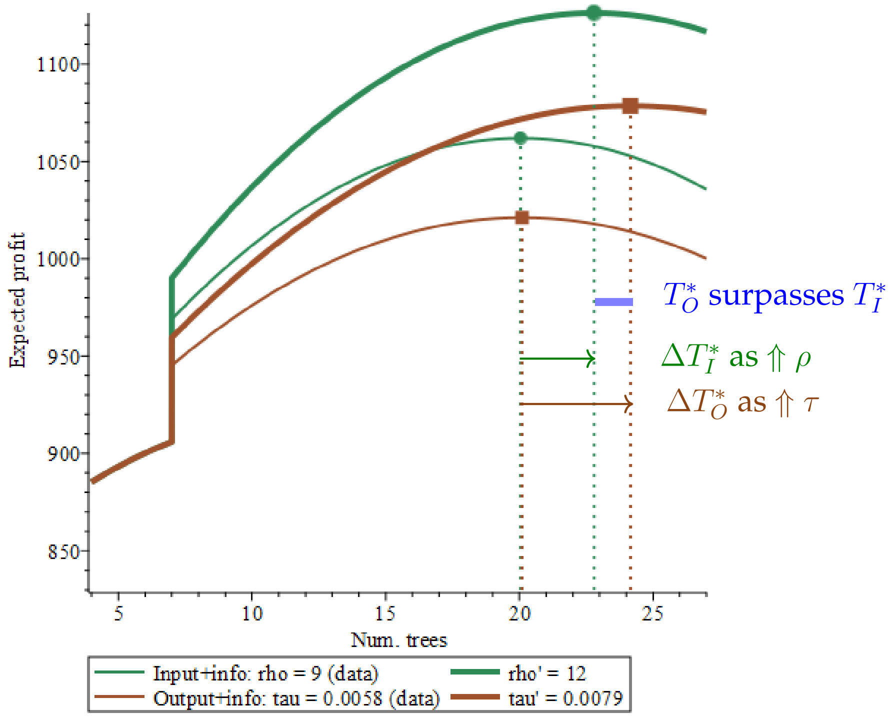


Figure 9: Expected profit function with information (lab vs higher subsidy)

Notes: This figure illustrates the relationship between farmers' expected profit and number of shade trees under the two subsidy schemes combined with information, based on calibrated parameters. Vertical dotted lines represent the optimal number of shade trees that maximize expected profit in each scenario. The thinner curves correspond to the lab subsidy level (*Input*: $\rho = 9$, *Output*: $\tau = 0.0058$), while the thicker curves represent a higher subsidy level (*Input*: $\rho = 12$, *Output*: $\tau = 0.0079$).

We focus on three measures of demand for a similar real-life subsidy program corresponding to the lab treatments. These measures are (1) WTP for a similar subsidy program, elicited during the *lab exit survey*; (2) expressed interest in a similar real-life subsidy program in a follow-up *phone survey* three months after the lab; and (3) whether the respondent requested more subsidy information via a *message* within three days after the phone survey. The last two outcomes were only collected in Sefwi. Table 8 summarizes the impacts on farmers' demand for a similar subsidy program across different lab-treatment arms. As farmers in the control group were not exposed to any subsidy interventions in the lab game, which could introduce selection bias, the main analysis excludes the control group and focuses on the four subsidy treatment arms.

WTP for a similar subsidy program was elicited through a series of unincentivized binary-choice questions, varying the entry cost until the respondent's answer flipped. In the lab game, the entry cost for either subsidy program was 70 tokens per one-acre cocoa plot, with over 95%

Table 8: Demand for different subsidies: willingness to pay (WTP) and interests

	Lab exit survey		Phone survey	
	(1) WTP	(2) WTP	(3) Interested	(4) Messaged
Output	-8.64**	-11.73*	-0.09**	-0.01
	(4.10)	(6.87)	(0.04)	(0.06)
Info	-3.24	-9.30	-0.06	0.11*
	(4.42)	(7.24)	(0.04)	(0.06)
Output x Info	2.83	17.49*	0.11*	-0.05
	(5.89)	(9.48)	(0.06)	(0.09)
Observations	1522	495	481	395
Mean (Input)	74.44	71.14	0.88	0.27
P-val: Input + Info = Output + Info	0.17	0.39	0.69	0.30
Sample	All	Sefwi	Sefwi	Sefwi

Notes: This table presents the treatment effects on farmers' demand for a similar subsidy program in real life. Willingness to pay (WTP) in columns (1) and (2) is measured by the maximum monetary value in GHC (capped by 400 GHC) a farmer is willing to pay for enrolling a one-acre cocoa plot in a similar subsidy program, collected in the lab exit survey. *Interested*, in column (3), indicates whether the farmer responded as interested in learning more about the subsidy program. *Messaged*, in column (4), indicates whether the farmer sent a message within three days after the phone survey to request more information about the subsidy program. Columns (3) and (4) are collected during the phone survey three months after the lab intervention. The analysis uses the full sample in column (1) and restricts the sample to Sefwi Bekwai in columns (2)–(4), as the phone survey was only conducted in Sefwi Bekwai. Regressions also control for strata fixed effects, imbalanced baseline controls, and PDSLASSO-selected baseline control variables. Standard errors in parentheses are clustered at the farmer level. "P-val," below each panel, reports the p-value for the group t-test for each treatment pair (listed in parentheses). Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

of respondents participating. Column (1) of Table 8 shows that compared to the *Input* group, farmers' WTP for a similar output subsidy program in real life is significantly lower by GHC 8.6 per acre, equivalent to an 11.5% decline. Additionally, there is no evidence that information nudging increases participants' interest in a similar real-life subsidy program, whether under input-based or output-based subsidies. The lower WTP under the output-based subsidy remains robust when considering alternative measures, such as an indicator for unwillingness to participate and an indicator of WTP equal to the maximum possible value in the survey (Appendix Table B.7, columns (1)–(2)).[39]

[39] The maximum enrollment cost we set in a series of binary-choice questions is GHC 400 per acre. There is one caveat regarding the WTP measure: Around 50% of respondents' WTP is at the maximum level, which could dampen the WTP difference across treatment arms.

In the Sefwi sample, the full-sample finding still persists, where farmers have lower WTP under the output-based subsidy compared to the input-based subsidy (Table 8, column (2)). Moreover, information nudging is more effective when combined with the output subsidy, leading to a significant 26.2% increase in WTP compared to the input-subsidy group mean. This contrasts with the insignificantly negative impact of information when combined with the input-based subsidy. In the phone survey, we find consistent evidence that a significantly lower proportion of participants (9 percentage points, or a 10.2% decrease) expressed interest under the output subsidy (Table 8, column (3)). Additionally, the interaction term $Output \times Info$ reflects a significantly larger impact of information on increasing farmers' interest in a similar real-life program, effectively narrowing the gap between the two subsidy treatments without information nudging. In the message phase, conditional on expressing interest in the program, 27% of respondents in the input-subsidy group sent a message to request further information (Table 8, column (4)) while information has a significant positive impact of 11 percentage points (a 40.7% increase) when combined with either subsidy program. It is worth noting that factors such as the cost of sending a message, technical issues, and social trust concerns may have contributed to the overall low response rate.

In addition, Appendix Table B.8 provides a summary of shares of farmers interested in different aspects of a similar subsidy program, segmented by treatment arms. Over 70% of respondents expressed interest in learning more about subsidy levels and costs, while less than 10% were concerned with noncompliance fines. This finding is supported by Appendix Figure B.8, which shows that over 50% of respondents ranked information about the subsidy level as their top priority, followed by participation costs and stakeholder information.

8.2 Lab-game income

We explore the treatment impacts on farmers' game income and nontargeted outcomes based on the lab-game measures as well. The lab setting enables us to discuss government spending and farmer welfare within the game. In the game, government spending per farmer equals the amount of subsidies paid minus the participation fees, which is essentially the net subsidy income to farmers. Table 9 shows that government spending per farmer is cheaper under the output subsidy, as less subsidy is paid out when yields are lower. The average government spending per tree is 3.7 tokens in the *Output* group, lower than the 5.3 tokens in the *Input* group. Consider the carbon sequestration of 8–14 kg of CO_2 per tree per year, either of the subsidy cost is well below the social cost of carbon reduced.

Table 9: Government subsidy spending: *Input* vs. *Output* subsidies (lab game)

	Gov subsidy spending		Subsidy spending per tree	
	(1)	(2)	(3)	(4)
Output	-26.84***	-27.94***	-1.56***	-1.61***
	(5.97)	(6.21)	(0.31)	(0.32)
Info		16.81***		0.32
		(4.36)		(0.22)
Output x Info		-5.40		-0.14
		(8.88)		(0.45)
Observations	1526	3044	1526	3044
Mean (Input)	104.25	104.25	5.30	5.30
Prob> F (Input + Info = Output + Info)		0.00		0.00

Notes: This table presents the treatment effects on government net subsidy spending (subsidy - enrollment fee). Regressions in columns (1) and (3) use the sample of the two treatment groups(*Input* and *Output* groups); regressions in columns (2) and (4) use the sample of four treatment arms except the control group. Standard errors in parentheses are clustered at the farmer level. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We use both expected production income and subsidy income to assess farmers' welfare, based on their expected cocoa bean harvests under different weather shocks (Table B.9). Our findings indicate that the output subsidy leads to larger subsidy income gains under normal weather and smaller subsidy income gains under harsh weather, when compared to the input subsidy. However, the impacts on total income are not statistically different between the two subsidies. This procyclical nature of the output-based subsidy does not translate into higher income volatility.

8.3 Spillover effects

We also find that information nudging has spillover effects on nontargeted outcomes, such as the number of fruit trees on a cocoa plot. Figure 10 shows that under both input and output subsidies, providing additional information on climate risks and shade benefits increased the number of fruit trees on cocoa farms by more than one tree per acre.

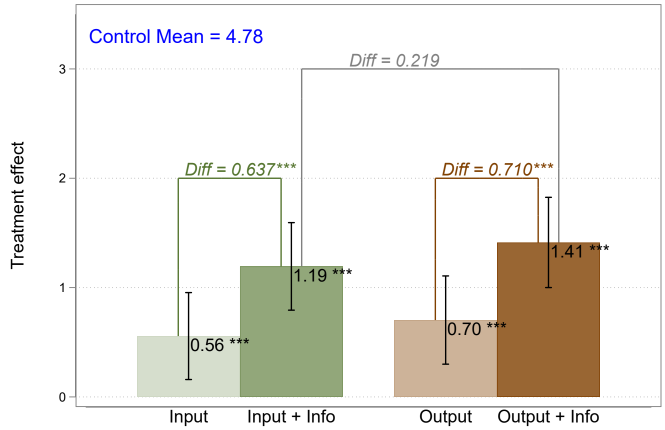


Figure 10: Fruit tree decisions (Game)

Notes: This figure presents the treatment effects on the number of tall fruit trees planted for shade on a one-acre cocoa plot in the lab game, based on the regression following equation 1a. Regressions include prespecified land characteristics (e.g., soil type, distance to water source) and farming practices (e.g., rounds of weeding, spraying, pruning, and fertilizer type), strata fixed effects, imbalanced baseline controls, and PDSLASSO-selected baseline control variables. Standard errors are clustered at the farmer level. Each bar represents the treatment effect magnitude w.r.t. the control mean: input-based treatments (*Input*; *Input+Info*) are in green, and output-based treatments (*Output*; *Output+Info*) are in brown, with darker shades indicating information treatments. The error bars indicate 95% confidence intervals. Magnitudes and p-values for group differences between each pair are reported. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

9 Conclusion

Both input and output subsidies for climate adaptation demonstrate potential to achieve the objective of promoting sustainable practices. However, our study underscores that output subsidies, especially when complemented with information nudging on climate adaptation, work better to promote sustainable agricultural practices and enhance farmer welfare. The efficacy of the output subsidy relies heavily on individuals' capability to update their beliefs about climate risks and incorporate adaptation strategies into their production decisions. Our findings are further corroborated by the practical validation of our lab-game outcomes during the GGP, particularly through the distribution of forest tree seedlings in 2024.

Despite the great potential of output subsidies, our study reveals a significant disparity in farmers' willingness to adopt output subsidies compared to input subsidies. This is evidenced by lower initial WTP measures during the lab session and reduced sustained interest observed in the subsequent phone survey. Moreover, our findings suggest that informational nudges have not effectively stimulated farmer engagement or participation in subsidy programs. Therefore, further investigation into the underlying factors contributing to this lower demand under output-based subsidies is imperative.

These findings underscore the pivotal role of heterogeneous individual beliefs in shaping the effectiveness of different subsidy policies, with broader implications for the formulation and implementation of agro-environmental policies. Policy frameworks should meticulously consider the heterogeneity in individuals' beliefs while strategically deploying targeted information campaigns tailored to the needs of target populations. This is increasingly crucial in a global landscape marked by escalating climate risks, heightened uncertainty, and persistent information gaps, particularly those affecting less educated farmers with limited access to reliable information resources.

Moreover, financial constraints, information barriers, and other challenges are often intertwined and vary across regions. Therefore, it is necessary to consider localized frictions and requirements when implementing global practices like PES or certification programs across regions. Tailoring information campaigns to align with local comprehension levels and institutional capacities is essential for effective policy uptake and impact.

Equity issues in program enrollment and compensation distribution are growing concerns in local implementation or scaling up of compensation programs and other environmental policies. During the 2024 GGP tree seedling distribution, respondents expressed concerns about unequal benefits favoring individuals with closer ties to community leaders or chiefs, while many others lacked access to information and program benefits in previous years. Establishing robust monitoring systems is essential to enhancing local enforcement of sustainable programs and ensuring transparency and equitable distribution of benefits among the broader community.

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Appendices

Appendix A Information treatment script

[Climate Change Risk] Human activities are estimated to have caused approximately 1.0°C of global warming above that in the reference period 1850–1900. Global warming is likely to reach 1.5°C between 2030 and 2052 if greenhouse gas emission continues to increase at the current rate. Future warming will negatively affect food systems (including cocoa production) in Africa by shortening growing seasons, raining with extreme variability, and increasing water stress. In Ghana, scientists predicted:

- 30-50% decrease in rainfall in the beginning of rainy season
- 30-50% increase in rainfall in the month between the major and minor rainy seasons

In this game, climate scientists forecast that the likelihood that abnormal weather would happen in this region next year is around 20%. It is equal to the chance of randomly drawing a red ball from a black box with 1 red and 4 blue balls inside.

[Shade Tree Benefit] You might have to adjust your farming practice in response to climate change. Scientists also stated: Growing more shade trees on farms helps farmers to adapt to climate change by curbing the cocoa production decline due to harsh weather. More specifically, shade trees offer more benefits than just shade:

- Protect cocoa trees from strong sunlight and intensive rainfalls
- Bring down the farm temperature
- Retain groundwater and prevent soil erosion
- Enrich the soil and recycle nutrients
- Create habitats for pest predators, improve biodiversity

Appendix B Additional tables and figures

Table B.1: Balance table, farmer level (full sample)

	All	Control	Input		Output		Input + Info		Output + Info		N
	mean	mean	diff	(diff=0) p-val	diff	(diff=0) p-val	diff	(diff=0) p-val	diff	(diff=0) p-val	
Age	51.89	51.80	0.32	(0.51)	-0.08	(0.88)	-0.11	(0.82)	-0.66	(0.18)	1905
Experience	18.05	17.62	0.10	(0.88)	0.81	(0.20)	0.81	(0.19)	-0.47	(0.44)	1905
High school +	0.10	0.08	0.02	(0.30)	-0.00	(0.94)	-0.01	(0.78)	0.04*	(0.10)	1905
Num. farms	1.94	1.96	-0.01	(0.87)	-0.09	(0.19)	-0.05	(0.44)	-0.00	(0.99)	1905
Total land size (acre)	6.26	6.39	-0.04	(0.89)	-0.10	(0.69)	-0.15	(0.55)	-0.17	(0.49)	1905
Had land sharecropped	0.37	0.38	-0.03	(0.29)	0.00	(0.90)	-0.04	(0.23)	-0.01	(0.72)	1905
Avg. cocoa production (bags/acre)	1.79	1.78	0.08	(0.40)	-0.02	(0.86)	-0.04	(0.69)	-0.08	(0.35)	1905
Main farm income	4978.23	5264.92	-217.70	(0.57)	-416.13	(0.27)	-444.46	(0.24)	-681.09*	(0.06)	1905
Average shade	9.84	9.92	0.84	(0.30)	-0.99	(0.19)	-0.10	(0.91)	-0.33	(0.65)	1905
Shade benefit	7.06	6.87	0.20	(0.29)	-0.03	(0.87)	0.35*	(0.06)	0.24	(0.20)	1905
Received bonus from LBCs	0.47	0.45	0.03	(0.37)	0.01	(0.64)	0.03	(0.43)	0.00	(0.90)	1905
Household (HH) head	0.84	0.83	0.01	(0.66)	-0.00	(0.87)	-0.00	(0.98)	-0.00	(0.99)	1905
Num. HH male	1.14	1.12	0.06	(0.46)	0.01	(0.89)	0.01	(0.94)	-0.05	(0.53)	1905
Num. HH male labor on farm	0.57	0.57	-0.02	(0.83)	-0.02	(0.76)	-0.03	(0.76)	0.02	(0.85)	1905
Has nonagricultural income	0.45	0.45	-0.03	(0.47)	0.03	(0.36)	-0.00	(0.91)	-0.02	(0.55)	1905
Exper. conseq. dry weeks, 2022/23	7.77	7.77	0.08	(0.75)	-0.02	(0.92)	-0.18	(0.44)	0.04	(0.85)	1905
Expect more conseq. dry weeks	0.58	0.55	0.05	(0.21)	0.05	(0.18)	0.05	(0.20)	0.01	(0.71)	1905
Expect less rain	0.40	0.38	0.06	(0.10)	0.04	(0.31)	-0.01	(0.87)	0.03	(0.45)	1905
Had flood	0.49	0.50	-0.05	(0.16)	-0.01	(0.77)	0.04	(0.33)	-0.02	(0.62)	1905
Num. flood experienced	1.52	1.67	-0.39*	(0.06)	-0.07	(0.78)	-0.30	(0.14)	-0.12	(0.54)	1905
Belief - drought loss	-13.89	-13.98	-0.14	(0.91)	0.75	(0.53)	0.63	(0.59)	-0.70	(0.56)	1905
Climate change impact (scale)	-6.97	-7.55	0.76	(0.61)	0.68	(0.63)	0.40	(0.77)	1.51	(0.28)	1905
Attended any training	0.58	0.56	-0.02	(0.66)	0.01	(0.84)	0.05	(0.12)	-0.01	(0.75)	1905
Heard Green Ghana Program	0.38	0.37	0.05	(0.14)	-0.03	(0.31)	0.02	(0.49)	-0.02	(0.65)	1905
Productivity shock	0.00	0.02	0.06	(0.39)	-0.00	(0.96)	-0.10	(0.18)	-0.04	(0.60)	1905
F-test of joint sig. (p-value)				(0.51)		(0.94)		(0.41)		(0.91)	

Notes: This table provides a summary of summary statistics and balance tests. Each coefficient is from a separate regression of baseline farmer-level coveriates on treatment assignments and strata fixed effects based on the full sample from two sample districts. Top 1 percent of average cocoa production and main farm income are winsorized. Randomization is stratified by community area, gender, and total land size. *, **, and *** represent statistical significance at 10, 5, and 1 percent levels, respectively. Abbreviations include HH for household and LBC for licensed buying company.

Table B.2: Balance table, farmer level (Sefwi group)

	All	Control	Input		Output		Input + Info		Output + Info		N
	mean	mean	diff	(diff=0) p-val	diff	(diff=0) p-val	diff	(diff=0) p-val	diff	(diff=0) p-val	
Age	49.83	49.52	0.56	(0.51)	-1.03	(0.22)	-0.10	(0.91)	-0.53	(0.51)	617
Experience	19.85	20.43	0.00	(1.00)	-1.73*	(0.08)	-1.19	(0.20)	-1.57*	(0.09)	617
High school +	0.14	0.11	-0.01	(0.77)	0.03	(0.53)	0.03	(0.44)	0.07	(0.12)	617
Num. farms	1.94	1.92	-0.02	(0.89)	-0.05	(0.67)	0.11	(0.42)	-0.04	(0.76)	617
Total land size (acre)	5.92	6.08	-0.24	(0.50)	-0.12	(0.69)	-0.02	(0.96)	-0.39	(0.21)	617
Had land sharecropped	0.19	0.20	-0.01	(0.82)	0.03	(0.54)	0.02	(0.72)	-0.06	(0.22)	617
Avg. cocoa production (bags/acre)	1.60	1.61	0.11	(0.46)	-0.08	(0.57)	-0.19	(0.15)	-0.17	(0.18)	617
Main farm income	6922.90	7415.13	-611.23	(0.46)	-618.59	(0.44)	-1022.80	(0.19)	-1219.79	(0.11)	617
Average shade	7.41	7.06	1.01*	(0.09)	-0.17	(0.73)	0.91*	(0.09)	0.11	(0.81)	617
Shade benefit	7.54	7.72	-0.16	(0.57)	-0.50*	(0.08)	-0.35	(0.18)	-0.22	(0.39)	617
Received bonus from LBCs	0.72	0.70	0.02	(0.77)	0.04	(0.45)	0.02	(0.77)	0.04	(0.51)	617
Household (HH) head	0.75	0.73	0.03	(0.52)	0.04	(0.45)	0.01	(0.86)	0.02	(0.69)	617
Num. HH male	1.25	1.25	0.01	(0.94)	0.00	(0.99)	-0.05	(0.76)	-0.15	(0.32)	617
Num. HH male labor on farm	0.67	0.64	-0.05	(0.70)	0.13	(0.34)	0.07	(0.66)	-0.11	(0.40)	617
Has nonagricultural income	0.34	0.34	-0.00	(0.98)	0.03	(0.59)	-0.02	(0.75)	0.02	(0.77)	617
Exper. conseq. dry weeks, 2022/23	7.39	7.40	0.42	(0.25)	-0.01	(0.97)	-0.15	(0.65)	-0.32	(0.32)	617
Expect more conseq. dry weeks	0.51	0.51	0.02	(0.78)	-0.01	(0.83)	0.03	(0.58)	-0.09	(0.16)	617
Expect less rain	0.36	0.37	0.04	(0.56)	-0.01	(0.91)	-0.08	(0.21)	-0.02	(0.74)	617
Had flood	0.44	0.49	-0.08	(0.24)	-0.08	(0.19)	0.04	(0.48)	-0.11*	(0.07)	617
Num. flood experienced	1.01	1.05	0.00	(0.99)	-0.11	(0.58)	0.19	(0.35)	-0.04	(0.85)	617
Belief - drought loss	-9.05	-8.36	-0.82	(0.58)	0.81	(0.56)	-2.34	(0.14)	-0.74	(0.61)	617
Climate change impact (scale)	-4.27	-3.92	-0.76	(0.64)	0.12	(0.94)	-0.77	(0.64)	-0.48	(0.76)	617
Attended any training	0.71	0.70	-0.04	(0.42)	0.03	(0.52)	-0.01	(0.80)	-0.03	(0.59)	617
Heard Green Ghana Program	0.33	0.34	-0.01	(0.92)	-0.04	(0.44)	-0.05	(0.41)	0.01	(0.85)	617
Productivity shock	0.00	-0.01	0.13	(0.33)	-0.09	(0.48)	-0.03	(0.83)	0.10	(0.42)	617
F-test of joint sig. (p-value)				(0.64)		(0.70)		(0.31)		(0.48)	

Notes: This table provides a summary of summary statistics and balance tests. Each coefficient is from a separate regression of baseline farmer-level covariates on treatment assignments and strata fixed effects based on the respondents from the Sefwi district group. Top 1 percent of average cocoa production and main farm income are winsorized. Randomization is stratified by community area, gender, and total land size. *, **, and *** represent statistical significance at 10, 5, and 1 percent levels, respectively.

Table B.3: Attrition in follow-up rounds

	Two rounds			Three rounds	Four rounds (Sefwi)	
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Nkawkaw	Sefwi	Sefwi	Balanced	Unbalanced
Input	0.007*	0.008	0.004	0.010	0.019	0.019
	(0.004)	(0.006)	(0.004)	(0.009)	(0.015)	(0.015)
Output	0.000	0.000	0.000	0.007	0.021	0.020
	(0.003)	(0.005)	(0.001)	(0.006)	(0.013)	(0.013)
Input + Info	0.001	0.001	0.000	0.003	0.010	0.010
	(0.003)	(0.005)	(0.001)	(0.006)	(0.012)	(0.012)
Output + Info	0.001	0.001	0.000	-0.001	-0.006	-0.007
	(0.003)	(0.005)	(0.001)	(0.005)	(0.011)	(0.011)
Observations	3858	2622	1236	1854	2472	2429
Mean (Control)	0.004	0.006	0.000	0.005	0.029	0.030
P-val:	(0.534)	(0.684)	(0.888)	(0.549)	(0.117)	(0.119)

Notes: This table presents the cumulative attrition rates across treatment groups in the follow-up rounds in the two sample areas (Nkawkaw and Sefwi Bekwai). The dependent variable, *Attrition*, equals 1 if the respondent is not reachable, is deceased, or refused to participate in the survey. There are four rounds in total: The baseline and lab surveys were conducted in both areas, while another two follow-up rounds were conducted only in Sefwi. Regressions in columns (1)–(5) are based on a balanced panel of 1,929 farmers (1,311 in Nkawkaw and 618 in Sefwi) and their corresponding rounds. The regression in column (6) is based on an unbalanced subgroup, where the last round of tree-seedling distribution data is conditional on farmers signing up for a positive number of tree seedlings for their cocoa farms in the phone survey (round 3). Strata and round fixed effects are included in all regressions. *, **, and *** represent statistical significance at the 10, 5, and 1 percent levels, respectively.

Table B.4: Treatment effects of subsidies on forest trees in the lab (panel)

	Forest trees		
	(1) Num. trees	(2) High shade (18+)	(3) Ultra-high shade (25+)
		Panel A: Uniform land	
Input	8.35***	0.57***	0.12***
	(0.28)	(0.03)	(0.02)
Output	7.58***	0.52***	0.07***
	(0.26)	(0.03)	(0.01)
Observations	1146	1146	1146
Control Mean	10.17	0.05	0.01
P-val: Input = Output	0.01	0.17	0.01
		Panel B: Individual land	
Input	8.21***	0.54***	0.11***
	(0.28)	(0.03)	(0.02)
Output	7.51***	0.53***	0.09***
	(0.27)	(0.03)	(0.02)
Observations	1146	1146	1146
Control Mean	10.17	0.05	0.01
P-val: Input = Output	0.02	0.79	0.26

Notes: This table presents the treatment effects on forest shade tree planting decisions on a one-acre cocoa plot in the lab game, based on equation 1a. The regressions are at the game level. Sample includes three treatment groups: control, *Input* subsidy, and *Output* subsidy groups. Panel A includes game response for a uniform plot, while Panel B includes that for an individual plot with varied land characteristics. Regressions control for prespecified land characteristics (e.g., soil type, distance to water source) and farming practices (e.g., rounds of weeding, spraying, pruning, and fertilizer type), strata fixed effects, imbalanced baseline controls, and PDSLASSO-selected baseline control variables. Standard errors in parentheses are clustered at the farmer level. *Num. trees* is the number of forest trees planted on a given one-acre cocoa plot (column (1)). *High shade (18+)* equals 1 if planting at least 18 forest trees in the game, indicating adoption of the High shade level according to the shade criteria (see Table 1) (column (2)); *Ultra-high shade (25+)* equals 1 if planting at least 25 forest trees (column (3)). Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.5: Treatment effects of subsidies and information on forest trees in the lab, using five arms

	Forest trees		
	(1) Num. trees	(2) High shade (18+)	(3) Ultra-high shade (25+)
Input	8.37***	0.56***	0.12***
	(0.28)	(0.03)	(0.02)
Output	7.59***	0.53***	0.08***
	(0.27)	(0.02)	(0.02)
Input + Info	9.82***	0.72***	0.24***
	(0.30)	(0.02)	(0.02)
Output + Info	10.08***	0.74***	0.26***
	(0.28)	(0.02)	(0.02)
Observations	3810	3810	3810
Control Mean	10.17	0.05	0.01
P-val: Input = Output	0.01	0.27	0.04
P-val: Input = Input + Info	0.00	0.00	0.00
P-val: Output = Output + Info	0.00	0.00	0.00
P-val: Input + Info = Output + Info	0.40	0.40	0.31
P-val: Δ Input = Δ Output $\mid$ Info	0.01	0.17	0.04

Notes: This table presents the treatment effects on number of forest trees farmers decide to plant on a one-acre cocoa plot in the lab game, based on equation 1a. The regressions are at the game level. Sample includes all five treatment groups. Regressions control for prespecified land characteristics (e.g., soil type, distance to water source) and farming practices (e.g., rounds of weeding, spraying, pruning, and fertilizer type), strata fixed effects, imbalanced baseline controls, and PDSLASSO-selected baseline control variables. Standard errors are clustered at the farmer level. *Num. trees* is the number of forest trees planted on a given one-acre cocoa plot (Column (1)). *High shade (18+)* equals 1 if planting at least 18 forest trees in the game, indicating adoption of the High shade level according to the shade criteria (see Table 1) (Column (2)); *Ultra-high shade (25+)* equals 1 if planting at least 25 forest trees (Column (3)). Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.6: Treatment effects of information with subsidies on forest trees in the lab (panel)

	Forest trees		
	(1)	(2)	(3)
	Num. trees	High shade (18+)	Ultra-high shade (25+)
	Panel A: Uniform land		
Info	1.45***	0.15***	0.12***
	(0.32)	(0.03)	(0.02)
Output	-0.81***	-0.05	-0.05**
	(0.30)	(0.03)	(0.02)
Output x Info	1.14***	0.07*	0.09**
	(0.43)	(0.04)	(0.03)
Observations	1522	1522	1522
Mean (Input)	18.60	0.62	0.13
Mean (Control)	10.17	0.05	0.01
Prob> F (Input + Info = Output + Info)	0.28	0.28	0.20
	Panel B: Individual land		
Info	1.37***	0.16***	0.12***
	(0.32)	(0.03)	(0.02)
Output	-0.76**	-0.02	-0.03
	(0.30)	(0.03)	(0.02)
Output x Info	0.89**	0.02	0.04
	(0.44)	(0.04)	(0.03)
Observations	1522	1522	1522
Mean (Input)	18.60	0.62	0.13
Mean (Control)	10.17	0.05	0.01
Prob> F (Input + Info = Output + Info)	0.70	0.76	0.59

Notes: This table presents the treatment effects of information given two subsidies using the *Input* subsidy only as a reference group. The regressions are at the game level. Sample includes four treatment groups: *Input*, *Input+Info*, *Output*, and *Output+Info* groups. Panel A includes game response for a uniform plot, while Panel B includes that for an individual plot with varied land characteristics. Regressions control for prespecified land characteristics (e.g., soil type, distance to water source) and farming practices (e.g., rounds of weeding, spraying, pruning, and fertilizer type), strata fixed effects, imbalanced baseline controls, and PDSLASSO-selected baseline control variables. Standard errors in parentheses are clustered at the farmer level. *Num. trees* is the number of forest trees planted on a given one-acre cocoa plot (Column (1)). *High shade (18+)* equals 1 if planting at least 18 forest trees in the game, indicating adoption of the High shade level according to the shade criteria (see Table 1) (Column (2)); *Ultra-high shade (25+)* equals 1 if planting at least 25 forest trees (Column (3)). Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.7: Demand for different subsidies: Alternative willingness to pay (WTP) measures

	Alternative WTP measures	
	(1)	(2)
	$\mathbb{1}_{WTP=0}$	$\mathbb{1}_{WTP>=400}$
Input	-0.06***	0.06*
	(0.02)	(0.03)
Output	-0.02	0.05
	(0.02)	(0.03)
Input + Info	-0.03	0.07**
	(0.02)	(0.03)
Output + Info	-0.03*	0.02
	(0.02)	(0.03)
Observations	1905	1905
Control Mean	0.13	0.36
P-val: Input = Output	0.01	0.70
P-val: Input = Input + Info	0.04	0.84
P-val: Output = Output + Info	0.39	0.37
P-val: Input + Info = Output + Info	0.75	0.16

Notes: This table presents the lab treatment effects on farmers' demand for a similar subsidy program in real life measured by willingness to pay (WTP) elicited in the postgame exit survey during the lab session, using the full sample in all columns. The regressions consider two alternative WTP measures in addition to the one in column (1) of Table 8: *WTP = 0*, indicating no willingness to participate; *WTP* $\geq$ *400*, indicating a willingness to pay at least GHC 400, representing the highest subsidy demand. *Risk averse*, indicating whether the respondent is risk averse (i.e., with a certainty equivalent below median, based on a set of choices over two hypothetical lotteries), is controlled for to account for the potential role of risk attitudes in selecting these subsidy programs. Regressions also control for strata fixed effects, imbalanced baseline controls, and PDSLASSO-selected baseline control variables. Standard errors in parentheses are clustered at the farmer level. "P-val," below each panel, reports the p-value for the group t-test for each treatment pair (listed in parentheses). Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.8: Interest in different aspects of subsidy program by treatment arm

	All	Control	Input		Output		Input + Info		Output + Info		N
	mean	mean	diff	(diff=0) p-val	diff	(diff=0) p-val	diff	(diff=0) p-val	diff	(diff=0) p-val	
Interested	0.84	0.79	0.07	(0.13)	0.04	(0.38)	0.07	(0.13)	0.07	(0.14)	606
Info - Subsidy level	0.84	0.79	0.07	(0.13)	0.03	(0.46)	0.06	(0.17)	0.06	(0.18)	606
Info - Farming requirement	0.51	0.51	0.10	(0.11)	0.04	(0.50)	-0.01	(0.88)	-0.08	(0.17)	606
Info - Participation cost	0.75	0.72	0.08	(0.12)	0.03	(0.58)	0.06	(0.23)	0.01	(0.81)	606
Info - Stakeholder	0.49	0.47	0.12*	(0.06)	0.00	(0.98)	-0.00	(0.93)	0.03	(0.62)	606
Info - Program duration	0.58	0.51	0.16**	(0.01)	0.04	(0.55)	0.11*	(0.08)	0.10	(0.10)	606
Info - Monitoring process	0.32	0.33	0.04	(0.52)	-0.06	(0.32)	-0.04	(0.54)	-0.02	(0.73)	606
Info - Noncompliance fines	0.07	0.05	0.08**	(0.03)	0.05	(0.12)	0.01	(0.78)	0.01	(0.81)	606

Notes: This table presents summary statistics for farmers' interests in learning more about specific aspects of a similar subsidy program in real life, by treatment arms. The sample includes respondents who completed the phone survey in Sefwi Bekwai. Each coefficient is from a separate regression of farmers' interest in different aspects on treatment assignments and strata fixed effects. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.9: Game income decomposition: Input vs. output subsidy

	Normal weather			Harsh weather		
	(1) Production income	(2) Subsidy income	(3) Total income	(4) Production income	(5) Subsidy income	(6) Total income
Input	217.30**	101.30***	318.74***	140.26**	102.34***	242.69***
	(87.34)	(4.28)	(88.44)	(61.03)	(3.55)	(61.88)
Output	185.38**	119.88***	306.52***	118.97**	63.18***	183.01***
	(86.31)	(7.62)	(91.17)	(60.33)	(5.38)	(63.72)
Observations	1562	1562	1562	1562	1562	1562
Mean (Control)	1276.41	0.00	1276.41	838.58	0.00	838.58
Prob> F (Input = Output)	0.72	0.03	0.90	0.73	0.00	0.37

Notes: This table presents the treatment effects on farmers' total income and income decomposition under different weather scenarios, measured by hypothetical game tokens. Production income includes proceed from selling harvested cocoa beans at the standard price, and the cost of planting shade trees. Subsidy income includes the lump sum reward amount under input-based subsidy, or price premium earned from harvested cocoa beans under the output-based subsidy, minus the program participation fee. Columns (1)–(3) show the results under normal weather, while columns (4)–(6) show the results under harsh weather. Regressions control for prespecified land characteristics (e.g., soil type, distance to water source) and farming practices (e.g., rounds of weeding, spraying, pruning, and fertilizer type), strata fixed effects, imbalanced baseline controls, and PDSLASSO-selected baseline control variables. Regressions use the sample of three treatment groups: control, *Input*, and *Output* groups. Standard errors in parentheses are clustered at the farmer level. Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.10: **Belief elicitation and survey questions**

Model		Survey		
Relevant parameter	Description	Survey Questions	Value	Source
z	Sensitivity of returns	(Shade benefit) On a scale from 0 to 10 (totally agree), please indicate your agreement on "Average cocoa production would have declined less if more shade trees had been grown."	Categorized, 0–10	Baseline & Lab
		(Drought impact) To what extent do you think cocoa production would change due to one more dry week during the dry season?	Categorized, $\pm$[X]%	Baseline & Lab
σ	Rainfall variability	On a scale from 0 to 10 (totally agree), please indicate your agreement on "Rainfall patterns would become less predictable in the next 30 years compared to past 3 years."	Categorized, 0–10	Baseline & Lab
μ	Rainfall average level	In the next 30 years, how many consecutive dry weeks (almost no rain) do you expect to experience during the dry season? How many rainy days do you expect to experience in a typical month during the dry season?	Continuous	Baseline
Θ	Belief set	(Perceived production function with respect to shade under normal or harsh weather) In a typical [normal/harsh] year, how many cocoa beans in bags do you expect to harvest from your main cocoa plot if [X] forest shade trees planted holding all else farming practice unchanged? (with farmer's main plot info listed)	Continuous	Baseline & Lab

Notes: This table provides a summary list of survey questions that reflect different belief components' measures.

Table B.11: Survey questions for subsidy interest and demand

Survey round	Questions	Value
Lab exit survey	Suppose the government is rolling out the above subsidy program in your community next year (this doesn't imply there will be such a subsidy program for sure). If the subsidy premium and criteria are as specified on the flyer, but the **enrollment fee** is different, please indicate whether you are willing to pay the enrollment fee to participate: *Are you willing to pay [X] GhC to enroll in such a subsidy program?*	Continuous, [0, 400] GhC
Phone survey	We would like to inform you of an opportunity of a possible subsidy program to be offered.	
	(*Input*) The government is collaborating with international organizations to initiate the *Tree Diversification Program* on cocoa farms, aimed at improving shade management. Farmers who decide to participate can **get rewarded** according to forest trees planted on the cocoa farms. *Do you want to learn more about this program?*	Dummy
	(*Output*) The government is collaborating with international organizations to initiate the *Sustainable Cocoa Initiatives* aimed at improving climate-smart and environmental friendly practices, for example, shade management. Farmers who decide to participate can get **additional price premium** for cocoa beans from these sustainable cocoa farms with more shade. *Do you want to learn more about this program?*	Dummy
Post-phone	Finally, if you want to learn more details about this program, you can reply [message key] to the following contact number [phone number]. (Enumerators took record of message responses from farmers)	Dummy

Notes: This table provides a summary of survey questions related to farmers' subsidy demand measures across multiple follow-up rounds.

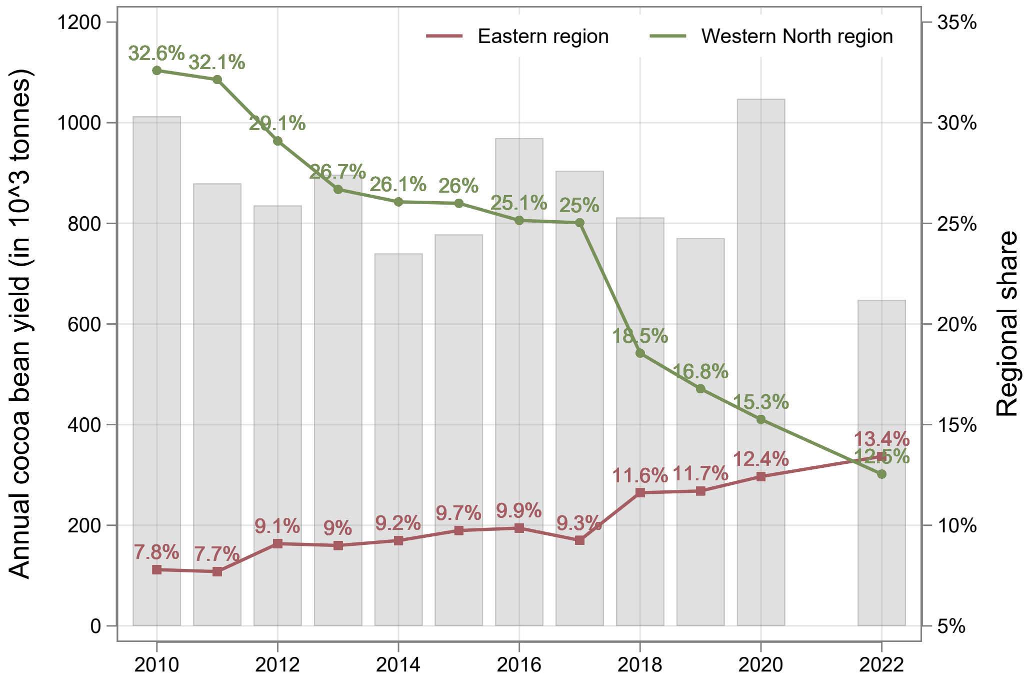
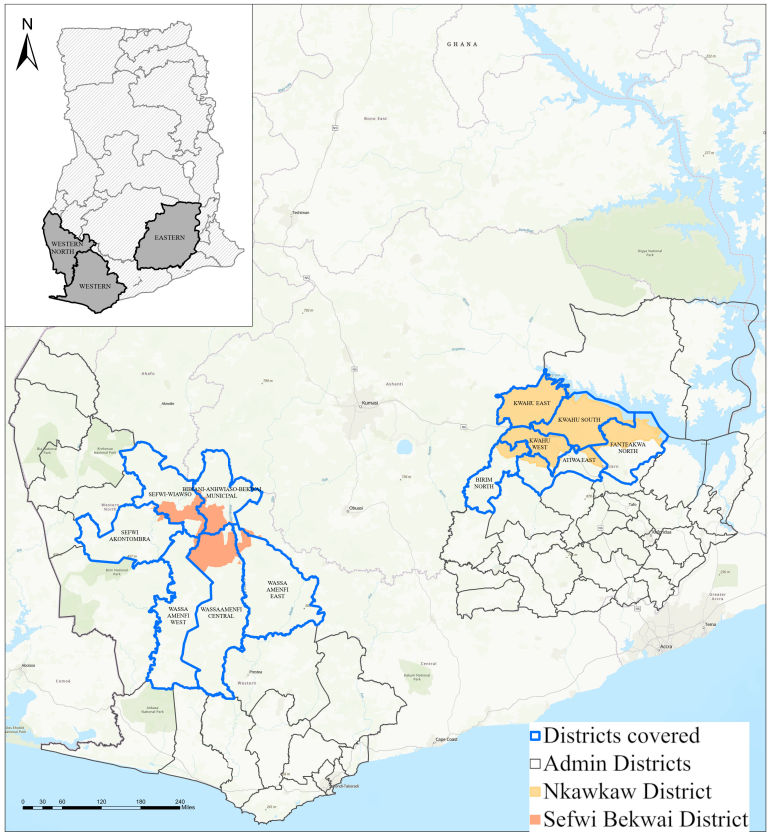


Figure B.1: Cocoa bean yield in Ghana and selected regions over time

Notes: This figure shows the total yield of cocoa beans in Ghana from 2010 to 2022, as well as the corresponding regional share for two sampled regions. The yield record for 2021 is missing because of COVID-19. Data source: Ghana Cocoa Board.

a. Selected cocoa districts



b. Cultivated farms of selected farmers in 30 communities

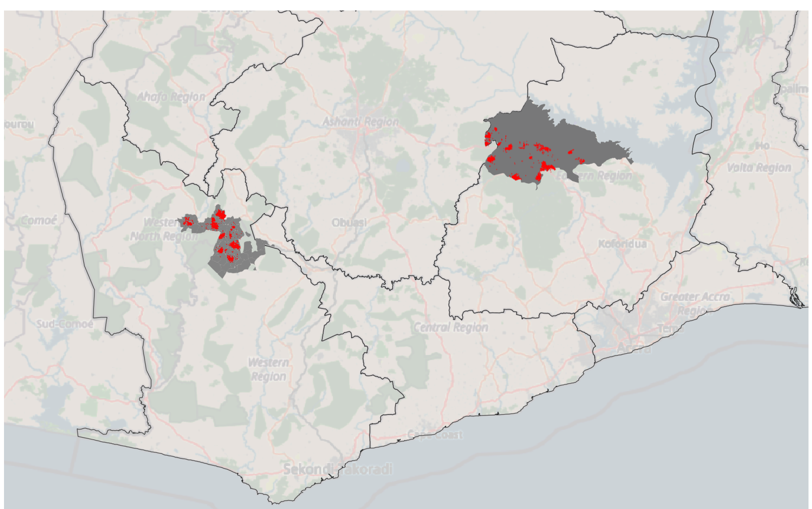
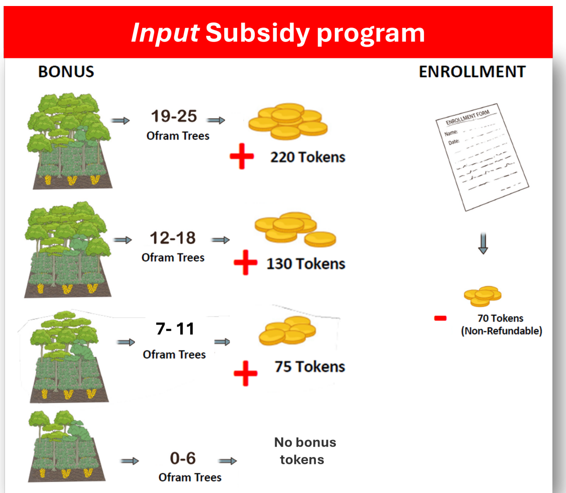


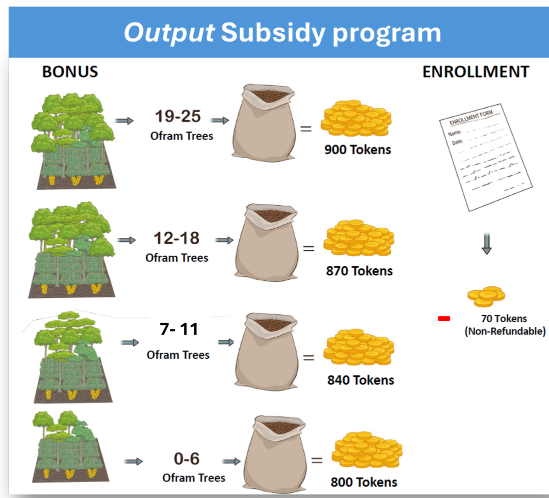
Figure B.2: Experimental Location

Notes: These maps display the geographical locations of the sampled districts and communities. Figure B.2a shows two regions in Ghana, highlighting the total cultivated cocoa area of the two sampled cocoa districts, with Nkawkaw in orange and Sefwi Bekwai in pink, and maps the correlation between cocoa districts defined by COCOBOD and administrative districts. Figure B.2b highlights the cultivated farms of sample farmers from 30 randomly-selected large-size communities in red. Specifically, cocoa districts, as defined by COCOBOD, differ from administrative districts. For example, the Nkawkaw district (colored in orange) covers six administrative districts in the Eastern Region: Kwahu East, Kwahu South, Kwahu West, Fanteakwa North, Atiwa East, and Birim North (blue boundaries).

a. Input Subsidy



b. Output subsidy



c. Information intervention

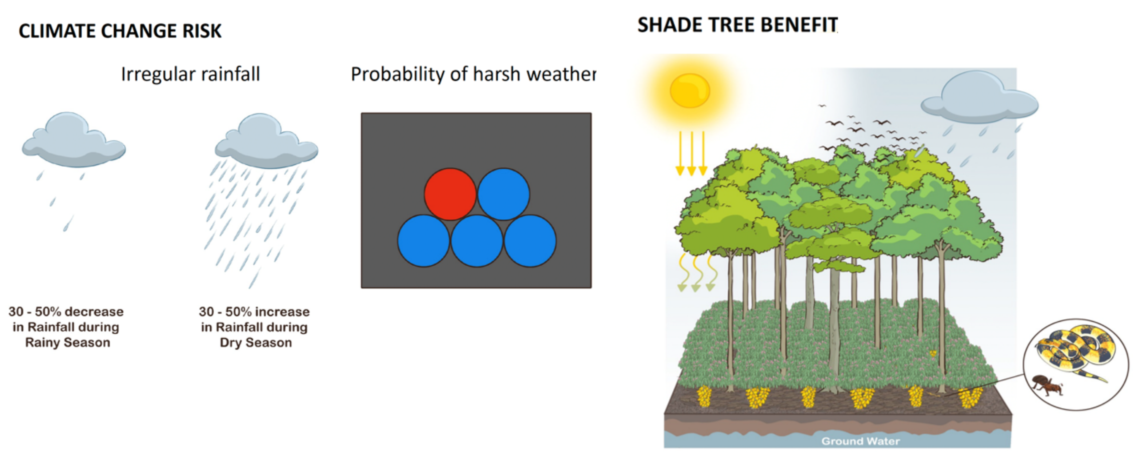


Figure B.3: Illustrative sample of subsidy and information interventions

Notes: This set of figures presents the illustrative example illustrating the experiment design. More detail about the two different subsidy programs is discussed in Section 3.1, and the information intervention is introduced in Section 3.2. A full script of the information can be found in Appendix A.

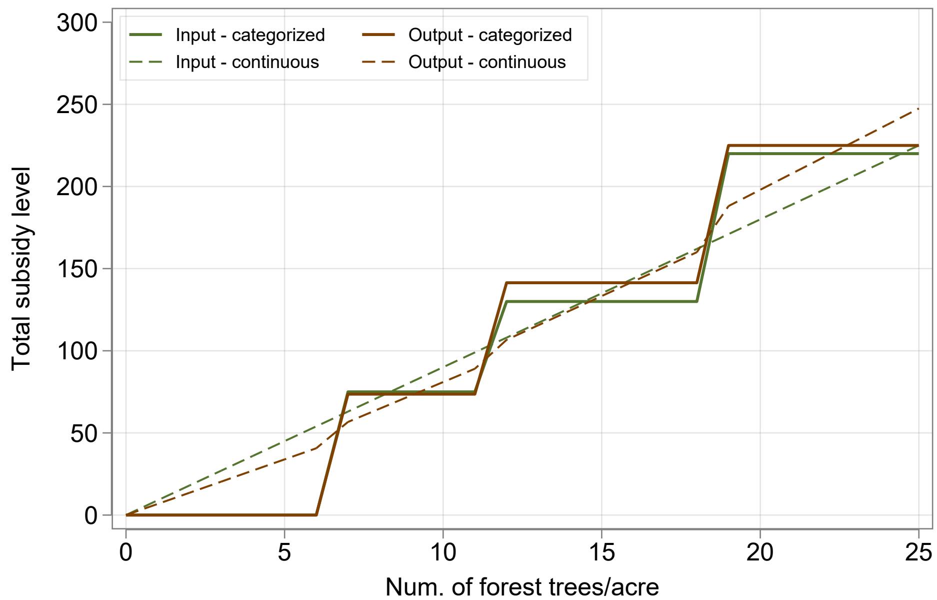
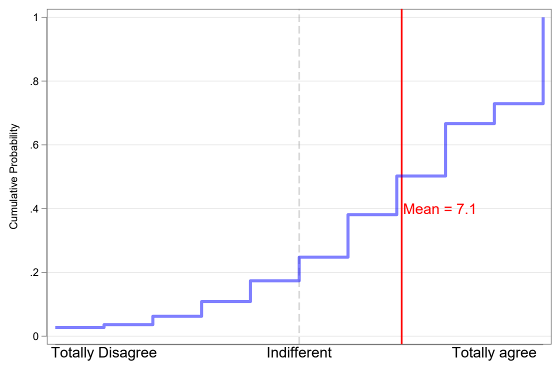


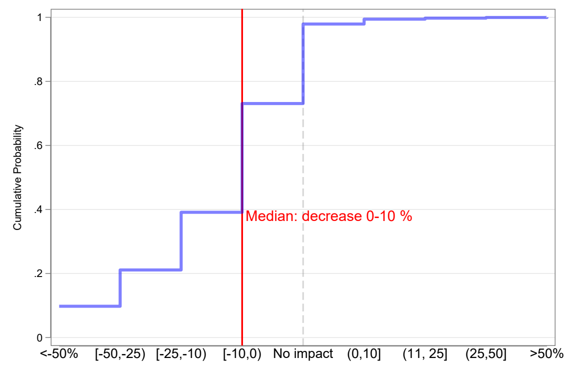
Figure B.4: Comparison of total subsidy income across two subsidies

Notes: This figure illustrates the similar levels of total subsidy income for farmers with average productivity across different shade categories, based on their baseline self-reported yields and shade levels. The dashed lines represent the continuous subsidy levels, serving as a proxy for the categorized subsidies used in the lab experiment.

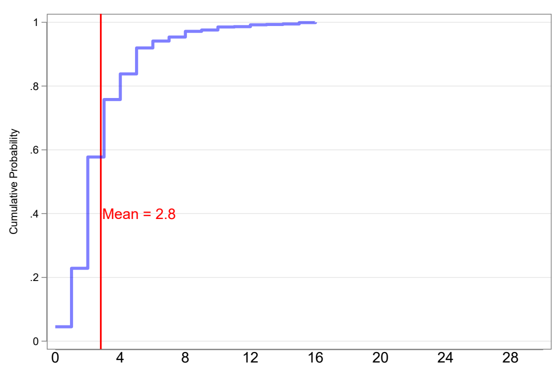
a. Shade benefit under drought (scale 0–10)



b. Drought impact on yield (%)



c. Num. rainy days/month in dry season



d. Less predictable future rainfall (scale 0–10)

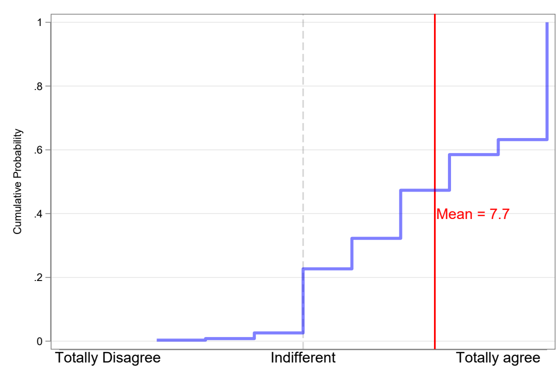
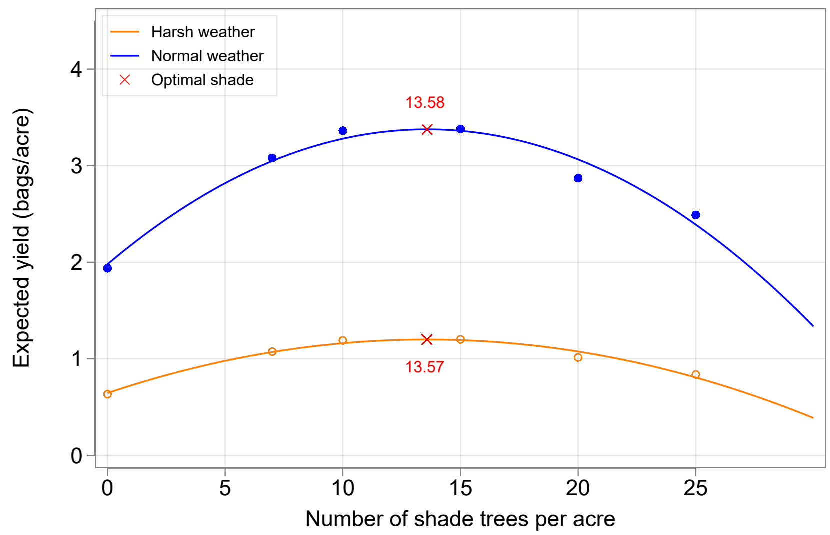


Figure B.5: Distribution of different belief component measures (Baseline)

Notes: This set of figures shows the cumulative distribution of farmers' different belief components measured in the baseline survey.

a. Average estimated production function



b. Distribution of estimated optimal shade trees

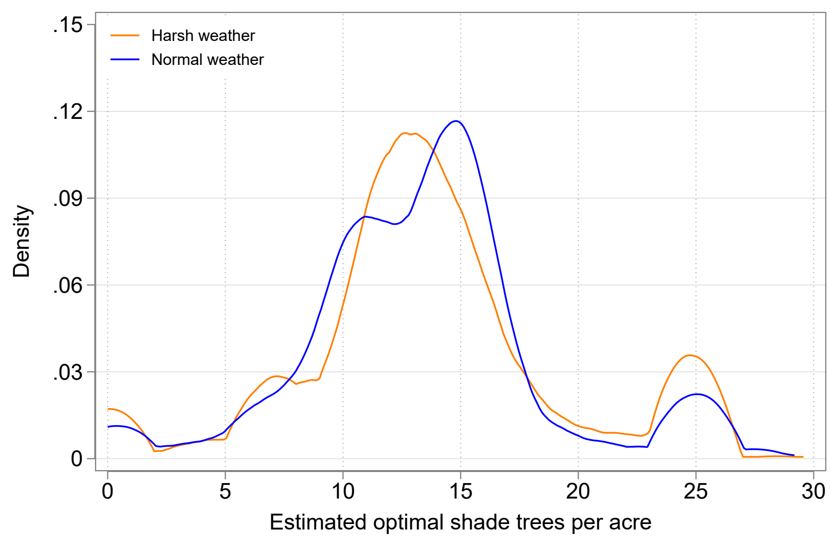


Figure B.6: Production function and distribution of optimal shade level

Notes: This set of figures shows farmers' prior perceived production function with regard to shade levels, measured by number of forest trees per acre. Panel (a) plots the average expected yield (number of bags per acre) for farmers' main cocoa plots at different shade levels under harsh and normal weather conditions, reported during baseline. The curves are the average of fitted production curves for farmers. Optimal shade is defined as the number of shade trees per acre achieving highest yield. Panel (b) presents the distribution of farmers' perceived optimal shade levels under normal and harsh weather reported during baseline, respectively.

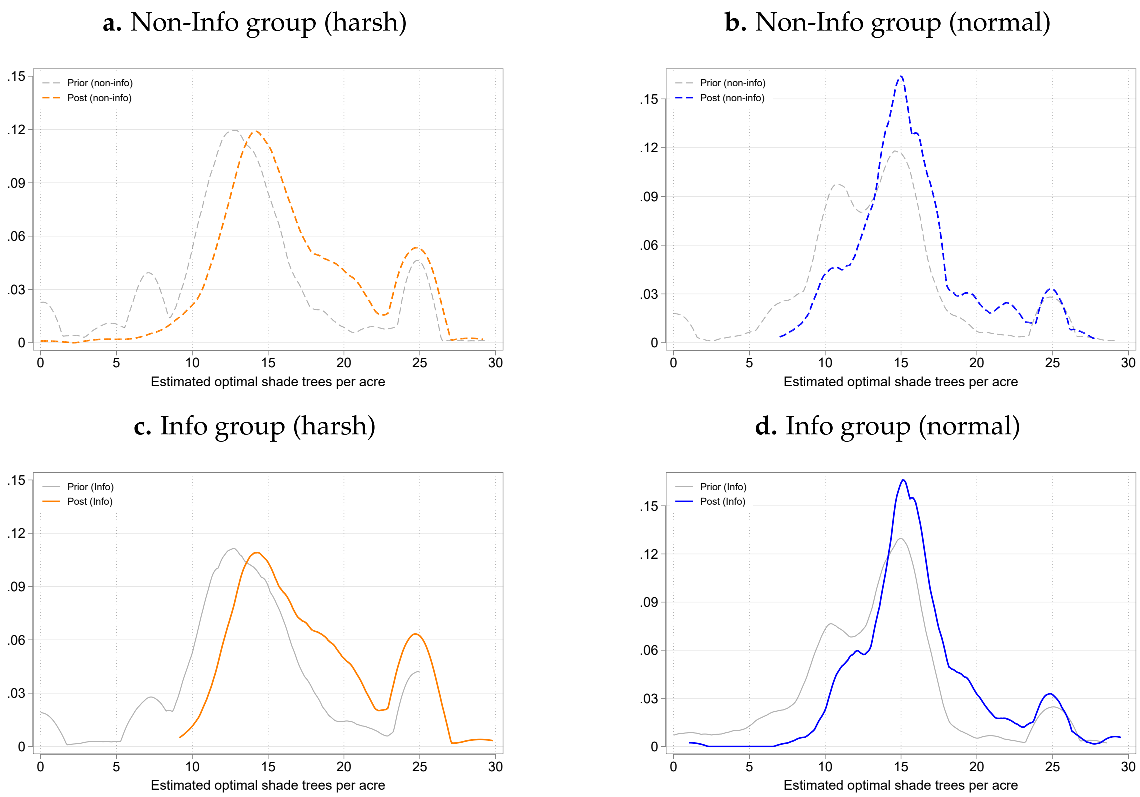


Figure B.7: Prior and posterior distributions of optimal shade under different weather

Notes: This set of figures shows the distribution of optimal shade level (number of forest trees per acre) implied from self-reported production function, under normal and harsh weather, respectively. Prior is collected during baseline survey. Posterior is collected during lab exit survey after the game. Panels (a) and (b) are based on *Input* and *Output* treatment groups. Panels (c) and (d) are based on *Input+Info* and *Output+Info* treatment groups.

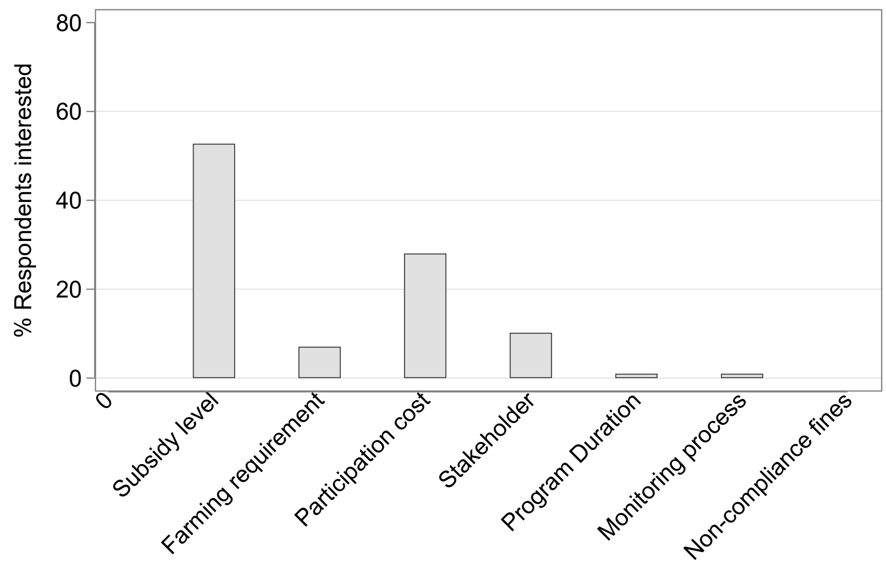
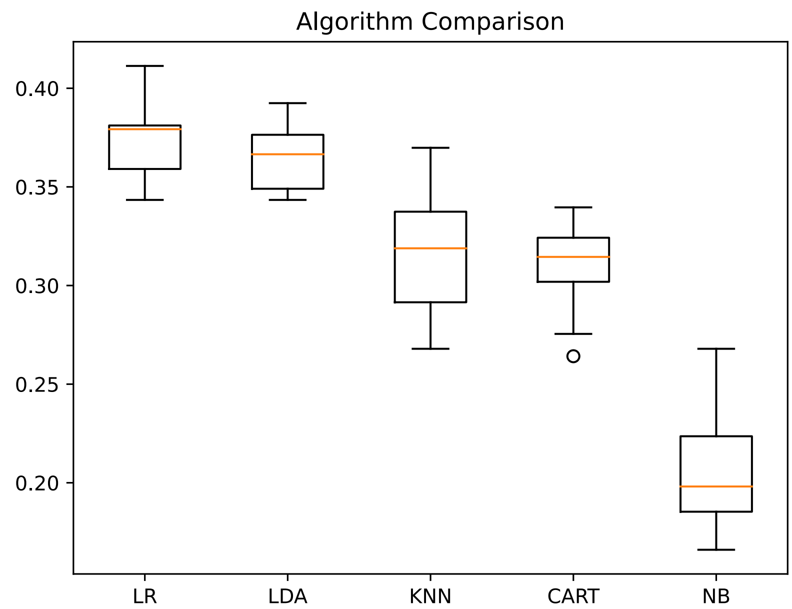


Figure B.8: Distribution of respondents' top-ranked subsidy information pieces

Notes: This figure shows the share of respondents who selected and ranked each subsidy information piece. The sample includes 606 respondents who completed the phone survey (Round 3, conducted in June 2024) in the Sefwi Bekwai district.

a. Region - Nkawkaw



b. Region - Sefwi

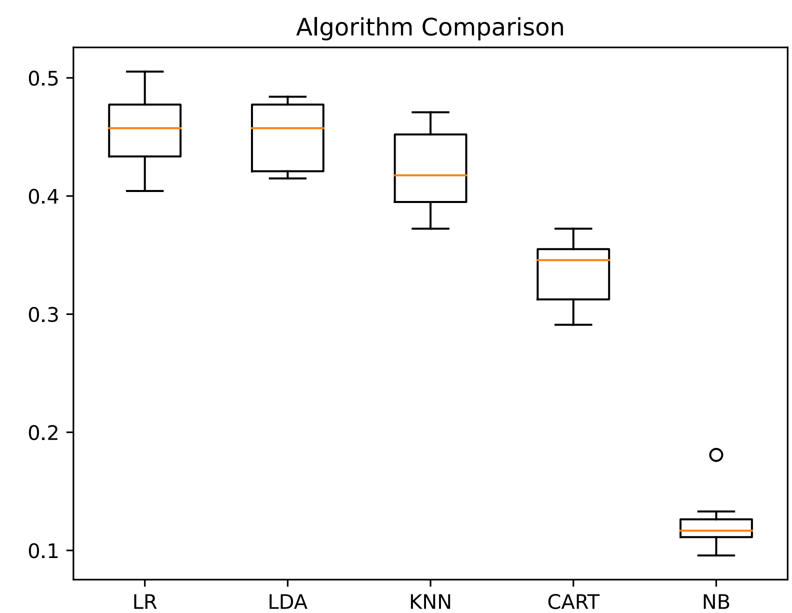


Figure B.9: Machine learning models cross validation score

Notes: This figure plots the cross validation scores for different machine learning models. A higher score represents higher accuracy. Panel (a) is for Nkawkaw and Panel (b) is for Sefwi Bekwai. LR is Logistic Regression. LDA is Linear Discriminant Analysis. KNN is K Neighbors Classifier. CART is Classification and Regression Trees Classifier. NB is Gaussian Naive Bayes. While LR and LDA both perform well, we selected LDA for the lab-in-the-field because of its relatively tighter confidence interval.

Appendix C Full derivatives of the model

Under *Input*,

$$
\begin{aligned}
\frac{\partial T_I^*}{\partial z} &= \frac{p\mu}{2c(\mu^2-\sigma^2)} > 0 \text{ since } \mu > \sigma > 0 \\
\frac{\partial T_I^*}{\partial \sigma} &= \frac{p\mu\sigma z}{(\mu^2-\sigma^2)^2} > 0 \\
\implies \frac{\partial^2 T_I^*}{\partial z \partial \rho} = 0,\ \frac{\partial^2 T_I^*}{\partial \sigma \partial \rho} = 0
\end{aligned}
$$

Under *Output*,

$$
\begin{aligned}
\frac{\partial T_O^*}{\partial z} &= \frac{-p\mu(\mu^2-\sigma^2)G(\tau)}{2[c(\mu^2-\sigma^2)+\tau pA]^2} \\
\frac{\partial T_O^*}{\partial \sigma} &= \frac{-p\mu\sigma z G(\tau)}{[c(\mu^2-\sigma^2)+\tau pA]^2} \\
\text{where } G(\tau) &= -p(y+\theta T^m)\tau^2 + (c_2 T^m + c_1)\tau - c_2, A = z\mu - \theta(\mu^2-\sigma^2) \\
\implies \frac{\partial T_I^*}{\partial z}, \frac{\partial T_O^*}{\partial \sigma} & \text{ depends on } G(\tau)
\end{aligned}
$$

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