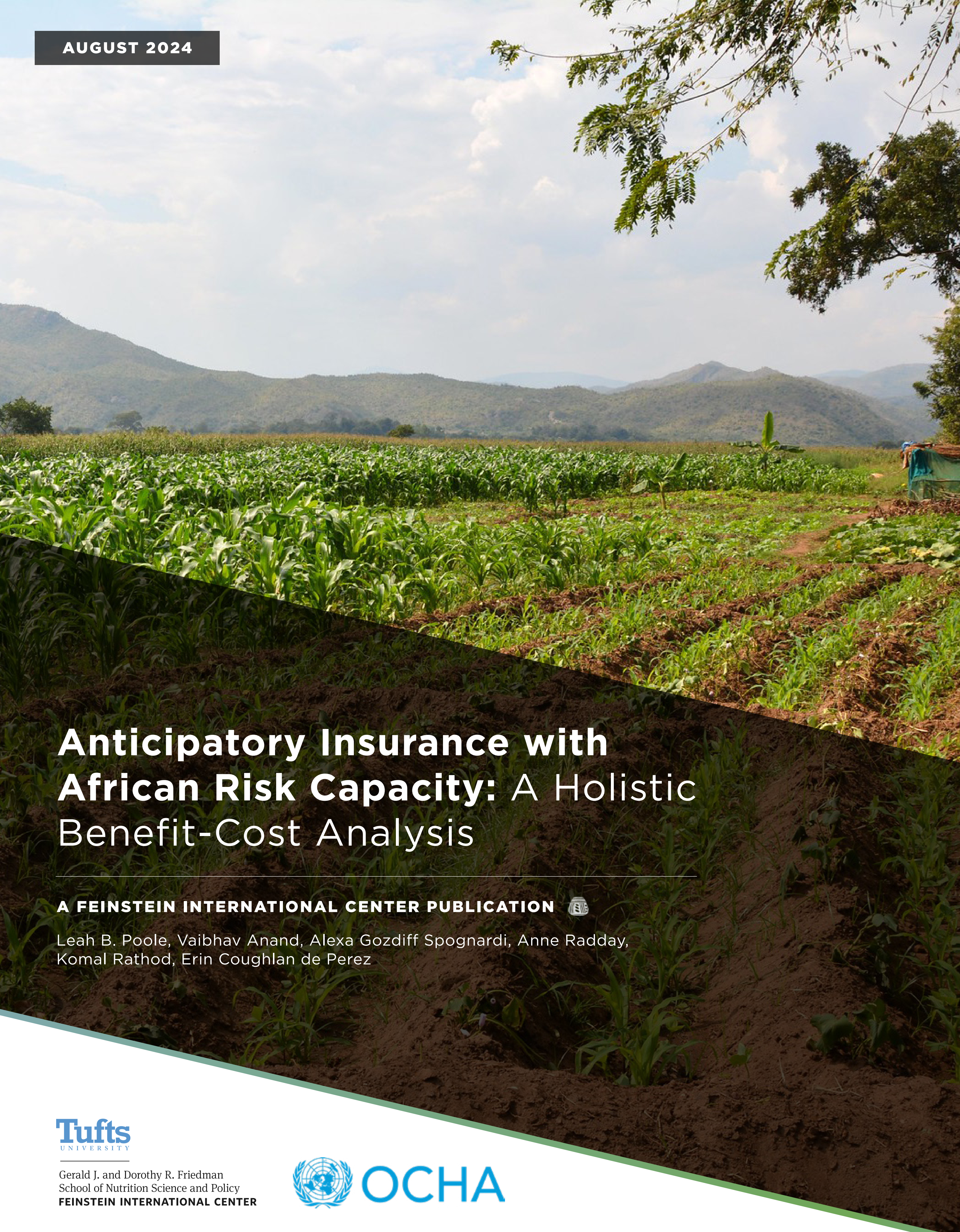

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Anticipatory Insurance with African Risk Capacity: A Holistic Benefit-Cost Analysis

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EXECUTIVE SUMMARY

African Risk Capacity has designed an anticipatory insurance (AI) product for drought in Malawi and Zambia; this report lays out the possible costs and benefits of such a product and a methodology for evaluating realized costs and benefits for the product, which is currently being piloted.* The costs and benefits assessed are intended to be holistic, considering not just the obvious and immediate costs and benefits but also those that may be indirect, long term, or less immediately apparent. Costs and benefits were assessed with an economic model, supported by qualitative data collected from key stakeholders that led to the production of a theory of change. We conclude by proposing a monitoring and evaluation (M&E) framework that can be adapted and utilized to assess the realized costs and benefits in the event anticipatory insurance is implemented. This initiative is a result of a partnership between OCHA and ARC, with OCHA contributing expertise in scaling up coordinated anticipatory action, financing product development and stakeholder engagement costs, and investing in learning, such as the benefit-cost analysis presented in this study.

Key Outputs and Results Connected to the Theory of Change

Expected positive benefits of the AI product centered on reduced use of negative coping strategies by drought-affected populations and improved yields, which resulted from use of aid such as replanting using the AI payout immediately after drought affects the original crops. Critical assumptions identified in the theory of change that could potentially pose challenges or points of failure for the product included premium defaults and other administrative-related delays or errors, whereby individuals or entities fail to fulfill their financial or contractual obligations, disrupting the anticipated cash flow essential for success. Once a payout is triggered, timing and delays at every step of the implementation process can lead to misalignment between projected and actual outcomes. Relatedly, poor targeting systems have been identified as a significant barrier to taking timely action. Another point of caution arises from procurement issues, which may include challenges in sourcing necessary resources or services, hindering the ability to deliver aid to recipients. Additionally, there may be delays in the disbursal of funding and materials as well as issues with the efficacy of the farm-level actions (e.g., yields for the replanted foods). Qualitative interviews revealed a variety of suggestions for the design of an AI product, including the consideration of climate change in the selection of attachment points, complementarity to existing farm subsidies, inclusive targeting, public engagement, government coordination, avoiding procurement failures, and the effectiveness of replanting. One proposed approach to ensure that these assumptions hold is to consider pausing the product's development temporarily to improve speed and test the effectiveness of certain actions at different timings. Alternatively, African Risk Capacity (ARC) could explore strategies that minimize potential points of failure in the product's implementation, such as requiring countries to generate and maintain beneficiary lists in advance and providing administrative support to ensure that contractual errors do not disqualify the country from coverage. In order to ensure the product's success, and a benefit-cost ratio greater than 1, it will be beneficial to analyze the various pathways available, especially during implementation, and select the one with the fewest identified points of failure. This approach could enhance the likelihood of achieving intended outcomes at the highest benefit ratio.

Key Results Connected to the Economic Model

The benefit of an anticipatory insurance (AI) product originates from two main sources: (1) its ability to provide forecast information to decision-makers for early action, and (2) its insurance mechanism that offers financing for these actions when it is likely most needed. Thus, the relative advantage of the AI product to a country depends on the country's access to forecasts and its capacity for early action. The AI product is welfare improving in scenarios where a country lacks the capacity for early action—due to limited access to forecasts, financing, or the

** No payout has been triggered in the initial year, making it difficult to assess the full benefits of the project.*

institutional capabilities required for implementation. However, for countries that can utilize forecast information effectively and have the capacity for early action, the incremental benefit of the AI product may be limited. For such countries, the AI product proves beneficial primarily when forecast accuracy is high, but the available early actions have a lower benefit-to-cost ratio.

The economic analysis highlights the importance of having a robust capacity in order to take advantage of forecasts and proactively manage risks. This capacity may include access to forecasts, a supportive institutional framework, predetermined standard operating plans (SOPs), training programs, financial arrangements, and an effective last-mile delivery infrastructure. Many countries may lack this capacity, and reallocating resources from ex-post aid and other priorities to develop this proactive capacity can be challenging. The current pilot of the AI product can help bridge this gap. It offers an opportunity for countries and stakeholders to assess their current capabilities and commit to develop the necessary infrastructure and processes.

Key Recommendations Connected to the Monitoring and Evaluation Framework

We recommend monitoring and evaluating any anticipatory products that are introduced to the market to assess whether the stated assumptions were realized. Benefit-cost ratios for specific actions can be calculated based on post payout evaluations, providing further data on the effectiveness and potential areas of improvement in the development of novel AI products.

CONTENTS

INTRODUCTION

Background on African Risk Capacity (ARC) and Insurance

The African Risk Capacity (ARC) Group functions as a dedicated entity within the African Union to bolster government responses to extreme weather events and natural disasters. The group offers support to enhance African governments' abilities in proactive planning, readiness, and reaction to severe weather incidents. The group has two entities: ARC Agency and ARC Limited. ARC Agency is responsible for in-country capacity building while ARC Limited is a financial affiliate responsible for risk pooling and transfer services. By fostering cooperation and inventive funding mechanisms, the combined efforts of ARC Agency and ARC Limited empower nations to develop their disaster risk management frameworks to bolster financial assistance in times of catastrophe and safeguard the security and wellbeing of susceptible communities.

The ARC Group offers a traditional drought insurance product that is intended to provide financial protection and compensation to policyholders in the event of drought-related losses, helping them mitigate the economic impacts of reduced agricultural yields or loss of livestock and diminished livestock productivity, after the drought has occurred. The ARC Group is in the process of developing an anticipatory insurance (AI) product to be used as a complement to their traditional insurance product. The anticipatory approach is different from previous ARC strategies and innovative in comparison to current government and humanitarian responses in contexts for which the product is planned to pilot in that the insurance pays out when drought is predicted, via forecasts, to cause significant loss and damage rather than after the loss and damage has occurred. The AI product is the product of interest for this research project, but it is worth noting that these products are designed to complement one another to provide comprehensive coverage in the event of extreme weather events.

The Role of United Nations Office for the Coordination of Humanitarian Affairs (UN OCHA)

From the outset, ARC, anticipatory insurance, and this research have been supported by the United Nations Office for the Coordination of Humanitarian Affairs (OCHA). OCHA's expertise, connections, and resources were instrumental in shaping various aspects of the research. Their commitment to best practices ensured that this research is grounded in real-world experiences. OCHA's collaborative approach and support were vital in addressing the complexities and challenges presented in this report, making their contributions invaluable to its success.

Research Application

The primary aim of this research project is to assess various scenarios involving the costs and benefits associated with offering and implementing anticipatory drought insurance in Malawi and Zambia. The costs and benefits assessed are intended to be holistic, considering not just the obvious and immediate costs and benefits but also those that may be indirect, long-term, or less immediately apparent. Costs and benefits will be assessed with an economic model, supported by qualitative data collected from key stakeholders.

The results of this research are intended to guide government decision-makers as they navigate purchasing the product and developing contingency plans prior to the purchase of the product by providing insights into challenges and potential successes associated with the implementation of the product. The research may also offer a useful framework of considerations for the potential expansion of this initiative to other countries, but caution should be taken when generalizing results.

The project aims to answer the primary research questions in Table 1.

TABLE 1. Key research questions and methods utilized throughout the research project

	Research Question	Research Methods
01	What are the contextual factors that determine the efficacy of anticipatory insurance products for the betterment of Malawi/Zambia?	• Literature and document review • Key informant interviews • Workshop attendance
02	Considering a holistic assessment of costs and benefits, what are the optimal conditions for the anticipatory insurance product to prevent drought related food insecurity and/or negative coping mechanisms in Malawi/Zambia?	• Stakeholder engagement • Data analysis • Economic estimates

It is important to note that this research is rooted in hypothetical assumptions and models. To ensure the relevance and applicability of the findings, the research team recommends a mechanism for continuous monitoring and evaluation that tracks how the assumptions made in the model align with real-world scenarios if/when the anticipatory insurance product is implemented.

Overview of the Proposed Anticipatory Insurance (AI) Product

The AI product is characterized by several key features, summarized in figure 1, that enhance the countries' resilience against the adverse impacts of severe droughts.

Central to the product is an early warning and trigger mechanism, powered by the Africa RiskView (ARV) software. The software models risks by combining historical rainfall data with current satellite observations. ARV uses the Water Requirement Satisfaction Index (WRSI), a comprehensive drought index. This index employs a holistic assessment of factors like rainfall, evapotranspiration, and soil moisture to gauge the availability of water for crops during the critical growing season.

Capacity building and stakeholder engagement are offered through workshops that foster collaboration, skill enhancement, and data exchange, thus empowering stakeholders to effectively navigate the intricacies of the product. Stakeholder engagement also increases the visibility of the anticipatory product to government stakeholders, facilitating informed decision-making and fostering a shared commitment to disaster resilience. Additionally, ARC offers technical support to participating countries to shape risk transfer parameters.

Through this integrated approach, the product can activate early payouts. Coverage limits are not fixed amounts and depend on the amount of premium finance available as well as the risk profile of the country. The ARC Group and the AI product thus present a strategy that aims to anticipate the challenges of climate-related adversities and equip countries with the tools, knowledge, and partnerships necessary to address and overcome these challenges.

FIGURE 1. Summary of the key features of ARC's proposed anticipatory drought action plan

Drought prediction via Africa RiskView	**Capacity building and stakeholder engagement**	**Drought insurance coverage**
Drought forecasting software that models risks by combining historical rainfall data with current satellite observations	Through workshops and technical support, stakeholders are offered opportunities to collaborate while learning new skills	An innovative insurance product that provides up to US$6 million worth of coverage based on forecasted drought

Background on Malawi and Zambia

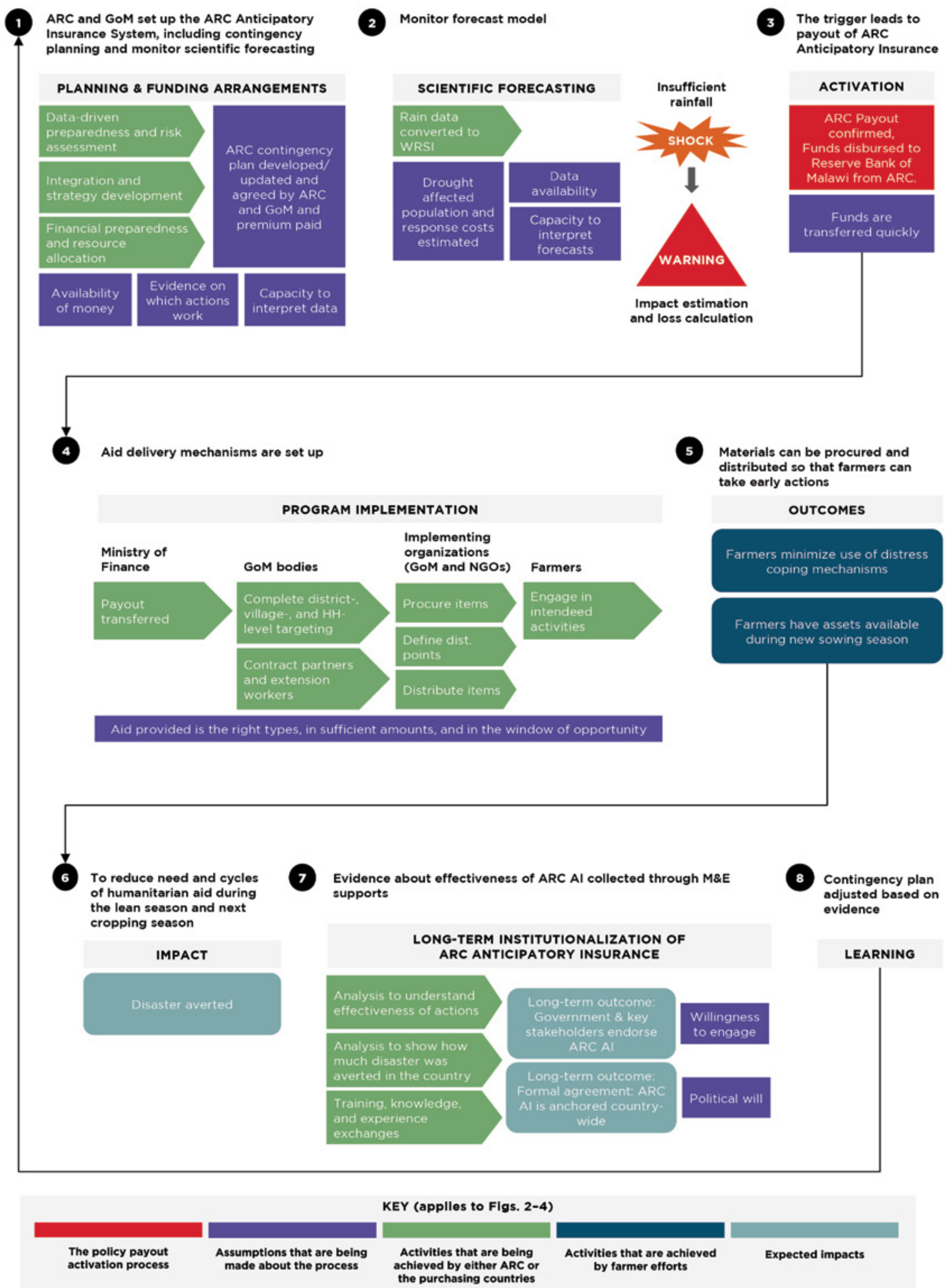
Malawi and Zambia, located in southern Africa, are regions prone to droughts that face persistent issues of food insecurity, affecting around 16 million Malawians to varying degrees, with classifications ranging from moderate to severely food insecure, and with 1.35 million Zambians being labeled as severely food insecure and in need of imminent humanitarian aid (World Bank 2023, European Commission, Knowledge for Policy 2023). This situation has been further complicated by rainfall deficits, with unprecedented droughts observed in both 2021 and 2022 (ReliefWeb 2022). They also exhibit significant poverty rates, with roughly 75% of Malawi's and 50% of Zambia's populations living below the international poverty line (ReliefWeb 2023). The nations' economic structures rely heavily on agriculture, which contributes more than 25% and 19% of Gross Domestic Product (GDP), respectively. In both countries, a considerable portion of the population depends on rain-fed small-scale farming for both sustenance and livelihoods (ReliefWeb 2023). However, the increased occurrence of climatic disasters, including prolonged droughts, has led to crop damage and failures, compounding the issues of poverty and food insecurity (*Tafirenyika* 2014).

RESULTS AND DISCUSSION

Theory of Change

Based on the comprehensive literature review, semistructured stakeholder interviews, and iterative feedback with ARC staff, we designed the following overarching theory of change to outline the timeline and assumptions for the anticipatory insurance product. See Figure 2. Key outcomes include minimizing the use of distress coping mechanisms among farmers, as well as increased assets available during the lean and sowing season. The theory of change also allows for iterative and reinforcing design, in which the evidence of impacts will inform future planning and funding arrangements.

FIGURE 2. Overarching theory of change for ARC anticipatory insurance, simplified



The overarching theory of change is informed by the following themes that were coded from the literature review and semistructured interviews. See Table 2.

TABLE 2. Qualitative interview takeaways, sorted by theme and subtheme, with resulting implications

SUBTHEME	SUMMARY	SELECTED QUOTE(S)	IMPLICATIONS
Theme: Farmer Context			
Climate change impacts	Climate change is affecting farming seasons, planting times, and changing the frequency and intensity of droughts.	"Due to climate change, the planting season has shifted to the end of October or November in some regions. Farmers sometimes have to wait until December for the onset of the rainy season."	How can attachment points for ARC consider the changing return periods of drought events? Can WRSI models properly represent both historical and current drought patterns?
Government support	Government subsidies, such as the Malawi Farm Input Subsidy Program, enable people to access essential inputs like seeds and fertilizer.	"Farmers often rely on the government for agricultural subsidies, particularly for essential inputs like seeds and fertilizers. When the government cannot provide these subsidies, it becomes challenging for farmers."	How will ARC inputs complement or replace existing farm subsidies from the government?
Farming has limited mechanization.	Traditional farming practices are prevalent in Malawi, with a heavy reliance on manual labor, limited mechanization, and low pesticide use.	"Many farmers rely on manual labor often due to the lack of access to education and modern farming equipment, which is limited by financial constraints."	How are farm laborers who do not have decision-making power on their farms included or excluded from the intervention? How is this reflected in targeting?
Farmers have limited access to finance.	Limited access to finance decreases agricultural productivity and economic development.	"The cost of farm inputs and limited access to finance are key factors affecting crop yields. Many farmers sell maize to afford seeds and fertilizer."	How does socioeconomic status impact utilization of the proposed intervention?

TABLE 2. Continued

SUBTHEME	SUMMARY	SELECTED QUOTE(S)	IMPLICATIONS
Theme: Critical Assumptions for Success			
ARC will not be effective without consultation with at-risk populations.	Need information dissemination about the insurance product to the public, coordination and collaboration among stakeholders, consultation with agriculture clusters, and needs assessments	"Dissemination of data is the challenge; most do not have access to the communication systems." "There also seemed to be a lack of scrutiny regarding the implementation details, as it appeared to be a policy-driven approach."	How will ARC engage with the public about this new product?
ARC will not be effective without government coordination.	Collaboration with organizations like OCHA and the government is essential but faces challenges like lack of consultation and information sharing. Ensuring political buy-in and understanding of the program at all levels is important for successful implementation.	"There is a concern that the preparatory work might not be completed ahead of time due to limited government capacity. Therefore, the success of the process must rely on the individuals involved being driven by a commitment to doing good rather than on internal incentives or financial motivations." "The period from January to April is short and critically important for this process to succeed. It necessitates careful planning, coordination, and alignment of all stakeholders to ensure the efficient transfer of funds and resources to address the anticipated challenges."	How can ARC coordinate with the government and ensure confidence in the new product?

TABLE 2. Continued

SUBTHEME	SUMMARY	SELECTED QUOTE(S)	IMPLICATIONS
Logistical constraints could limit the success of ARC.	Success factors will include timely transfer of funds, effective targeting delivery and implementation logistics, availability of inputs, and efficient transfer of resources.	"The transfer of funds needs to be done as quickly as possible, which is subject to the final implementation plan." "ARC needs to transfer the resources as quickly as possible, and obtain the right inputs on time so that farmers can make use of the remainder of the season."	How are benefits impacted if procurement of essential inputs fails? Can the anticipatory insurance product guarantee that farmers will receive inputs in time to replant?
Accurate forecasting will be required for success.	Africa RiskView is instrumental in modeling the impact of droughts, and their forecasts will need to be accurate for the anticipatory insurance product to succeed.	"It's essential that by mid-January, we should be in a position where we are able to evaluate the status of the situation on the ground. A crucial assumption is that the forecasting model accurately matches the situation on the ground."	Do all stakeholders understand the magnitude of the basis risk?
ARC should evaluate success.	Evaluation exercises are crucial to assessing the effectiveness of interventions and ensuring support reaches the right beneficiaries.	"Give room for independent evaluation for stakeholders to ensure that they are doing the right thing and that the support is going to the right people on the ground. Climatic shocks are here to stay, and we can only improve on the implementation."	Can ARC do a rigorous-enough evaluation to properly estimate the benefits after a payout?

TABLE 2. Continued

SUBTHEME	SUMMARY	SELECTED QUOTE(S)	IMPLICATIONS
Theme: Anticipatory Action Could Have Positive Impacts			
ARC could help avoid sowing failure.	Rather than waiting for the crops to fail, the anticipatory insurance payout would enable replanting and harvesting in what would have otherwise been a failed season.	"The historical drought is December to mid-January. In case of sowing failure around this time, the payout can be used from March to May. Payouts allow farmers to salvage part of the season rather than waiting for the end of the season. There are some crops and varieties that can be planted to salvage the season with residual moisture." "There would be an early payout so that farmers can make the best use of season."	Will the seeds and inputs produce sufficient yield on the timeline expected for the payout?
ARC could help prevent negative coping mechanisms.	Maintaining farmer incomes can help people avoid negative coping mechanisms, such as the sale of productive assets, that have long-term negative consequences.	"Providing for immediate needs so that the household does not use negative coping mechanisms (consumption of foods that are not good foods, wild foods, households may revert to selling bicycles, radios, and other assets in their households)."	Is the expected benefit substantial enough to affect the use of negative coping mechanisms?
ARC could improve food security.	With improved harvests during drought years, farmers and their families will have greater incomes and greater food consumption.	"Responding early could elevate farmer wellbeing and reduce significantly the amount of finance needed to respond at the end of the season."	Will the provision of two types of crops (maize and tubers) improve dietary diversity?

Based on the overarching theory of change and the context-specific actions proposed in Malawi, we developed a theory of change for the anticipatory actions proposed in Malawi. See Figures 3 and 4.

FIGURE 3. Expanded theory of change for Malawi

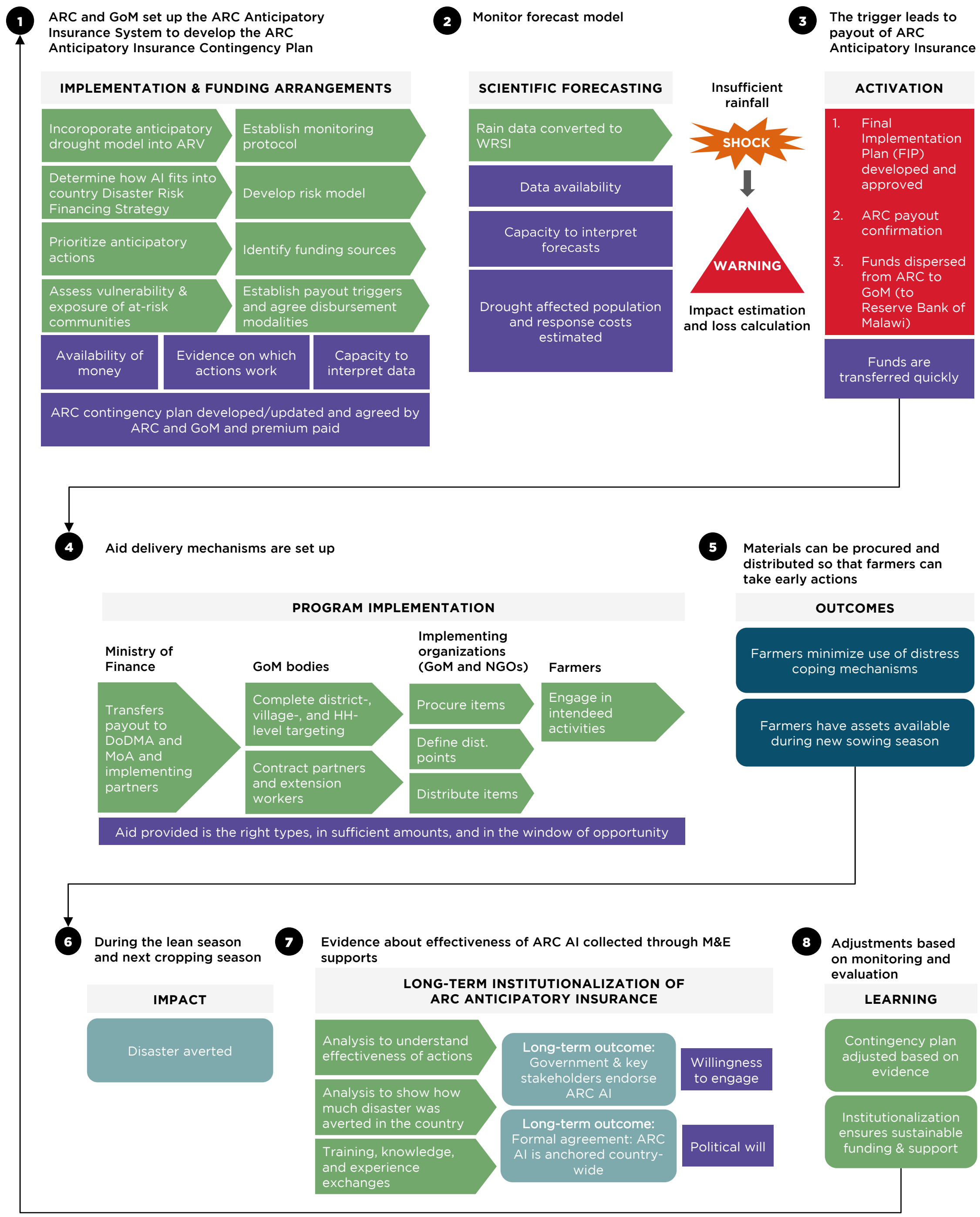
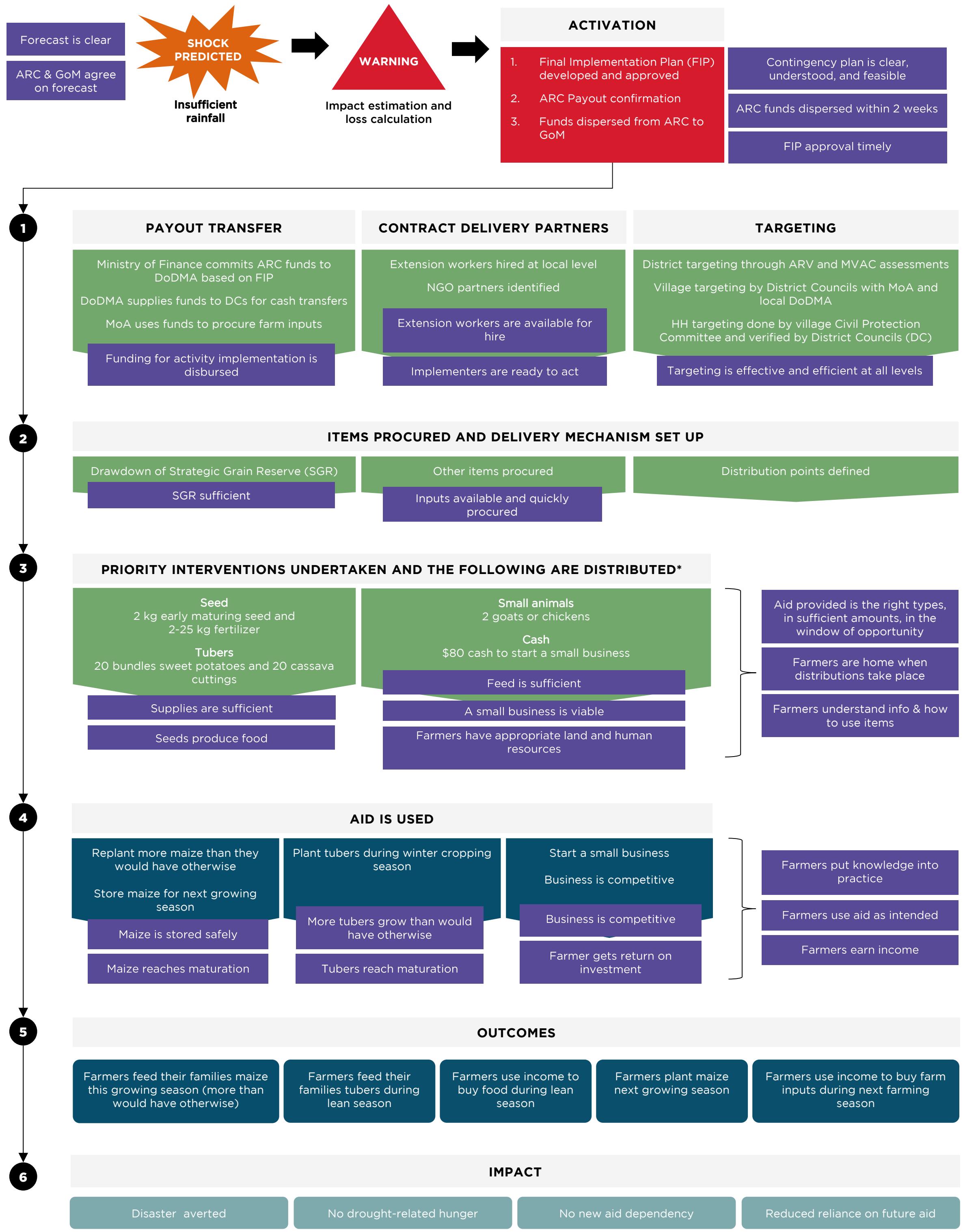


FIGURE 4. Expanded theory of change for Malawi: Details of implementation



*Participants will not receive every intervention. The intervention type received is subject to availability and feasibility of delivery.

Each purple box in the figures above represents an assumption we have made about the process, and these identified assumptions could potentially pose challenges or points of failure for the product. Critical assumptions identified in the theory of change that could potentially pose challenges or points of failure for the product included delays in the disbursal of funding and materials as well as efficacy of the farm-level actions (e.g., yields for the replanted foods). Qualitative interviews revealed a variety of suggestions for the design of an AI product, including the consideration of climate change in the selection of attachment points, complementarity to existing farm subsidies, inclusive targeting, public engagement, government coordination, avoiding procurement failures, and the effectiveness of replanting. One proposed approach is to consider pausing the product's development temporarily, allowing for the enhancement of country capacity to better align with overall goals. Alternatively, ARC could explore strategies that minimize potential points of failure in the product's implementation. It is worth considering the viability of financial resources within these conditions. Additionally, defining success and failure criteria as well as implementing a rigorous monitoring process for these success and failure criteria during implementation could help delineate potential outcomes.

In order to ensure the product's success, it might be beneficial to weigh the various pathways available and select the one with the fewest identified points of failure. This approach could enhance the likelihood of achieving intended outcomes at the highest benefit ratio.

Targeting and Gender Considerations

UN Women statistics highlight that women bear the burden of 50–70% of the world's work, yet they possess less than 20% of the land—a clear indication of gender disparities related to male-dominated ownership within societal structures *(UN Womenwatch | Rural Women - Facts & Figures: Rural Women and the Millennium Development Goals, n.d.)*. The theory of change underpinning our work does not fully account for these imbalances. Failure to adopt a gender-responsive approach not only disregards the significant contributions of women but also neglects to acknowledge the potential wellbeing costs associated with perpetuating such inequities.

Outcomes of various actions referenced in the theory of change could diverge significantly based on the gender of the recipient. For instance, targeting criteria in Malawi that prioritize women as beneficiaries may yield different results compared to similar initiatives in other regions where such gender-specific targeting is absent. While the exact impact remains speculative, it is reasonable to assume that the outcomes and overall effectiveness of interventions could vary substantially depending on the inclusion or exclusion of women as a primary focus. This disparity is not accounted for in our analysis but should be considered during contingency planning and in post distribution monitoring and evaluation.

Value of Forecast-Based Anticipatory Insurance

Model Setup and Benefit-Cost Ratios

We develop a stylized economic model to examine the value of the AI product. Our model builds over the economic analysis framework in Clarke and Hill (2013), which evaluates the benefits of ARC's traditional index insurance product. In our model, a country is endowed with a wealth of w, and faces a risk of drought, which results in the response cost l. The wealth w can be considered as the financial resources available to the country in a year. Existing literature suggests that a severe drought can reduce agricultural production and income by 30–45% (Devereux 2007; Clarke and Hill 2013). In our model, we assume that the response cost is 50% of the available financial resources, i.e., $w=0.5l$.[1] The unconditional probability of drought each year is p. It is the static probability of drought based on the long-run climatology of the country. Before the realization of the drought, the country receives a forecast of the potential response cost.[2] This

1 *The assumption of response cost being 50% of the available financial resources is somewhat conservative, especially when we are interested in the value addition from the AI product. The financial resources here can be thought of as the total financial wealth (or budget) that is available for consumption to the country. We show in the Appendix that a lower response cost assumption (i.e., $l=0.5w$) does not change our results. In fact, the AI product is more valuable in situations where the response cost is higher.*

2 *The updated probability may be thought of as the probability of drought conditional on available information about future weather in the country, e.g., the El Nino forecast. For now, no seasonal forecast is used in the model, though doing so is a future direction being considered by ARC.*

forecasted response cost is based on the updated forecast probability (ϕ) of the drought in that year. The country can take forecast-based anticipatory actions (or early actions) that result in a benefit of β per dollar of investment, in the form of reduction in losses when a drought occurs, i.e., the benefit-to-cost ratio of early action is $\beta>1$ when the drought occurs. When the drought does not occur, the benefit-to-cost ratio is assumed to be 1.[3] The country may or may not have the capacity to finance these forecast-based early actions itself.

The country can also purchase an anticipatory insurance (AI) product that provides the financing as well as capacity-building support. The AI product provides an insurance payout if the predicted probability of drought (ϕ) exceeds a predetermined attachment probability (ϕ_{att}). The payment frequency of the AI product, then, is once in every 1/q years where $q=Prob(\phi>\phi_{att})$. Note that this setup is equivalent to an AI product that provides an insurance payout if the predicted response cost (I_ϕ) exceeds a predetermined attachment point (I_{att}). As long as each forecasted probability of drought (ϕ) can be mapped to a forecasted response cost I_ϕ, the two formalizations are similar.[4] The country chooses the proportion of response cost to cover through this insurance (the ceding ratio, δ) as well as the attachment point, ϕ_{att}.

For example, consider a drought with an annual return period of five years, i.e., static probability p=0.2. In a given year, based on El Nino predictions and other weather forecast information, the forecast probability ϕ of drought can be anywhere between 0 and 1, i.e., $\phi\in[0,1]$. The country can access the historical data on such forecasts to form a belief about the distribution of ϕ (and its skill) and then choose an attachment point ϕ_{att}, such that the return period of anticipatory action is 1/q, where $q=Prob(\phi>\phi_{att})$. This return period of anticipatory action 1/q will also depend on how skilled the forecast of drought is. Suppose the forecast is always perfect, i.e., it is 0 when there is no drought (80% of the times), and 1 when there is drought (20% of the times). Then, as long as the country chooses an attachment point greater than 0.2, the return period of anticipatory action is five years. However, if the forecast technology is not perfect and has a fairly low skill (forecasts ϕ are just distributed around p=0.2 narrowly), then a small attachment point (say, 0.1) may result in a return period of much shorter than five years, whereas a high attachment point (say, 0.8) may result in a return period of much longer than five years.

Assumptions on Benefit-Cost Ratio of Early Actions

Because the ARC anticipatory insurance product has not yet had a payout, there is no data on realized benefits to the population. However, we can rely on secondary studies to estimate a range of plausible benefit-cost ratios if all assumptions in the theory of change hold. To do this, we first rely on a systematic review by Hemming et al. in 2018 that carried out a meta-analysis of all studies on the effect of farm inputs, many of which were from Malawi. This study found that provision of farm inputs is associated with increased adoption of those impacts, and recipients reported an increase in yields that averaged to 0.11 standard deviations of their expected yield, across all studies. Farmer income also increased as a result of these farm inputs (Hemming et al. 2018).

It is reasonable to assume, based on this body of evidence, that there would be a positive impact on the yields and income of recipient farmers from the anticipatory insurance ARC program, if all assumptions in the theory of change are met (e.g., inputs arrive on time). A review of Malawi-specific studies found similar results, with one study estimating that a 1% increase in area planted for improved maize was associated with "a 0.34% increase in own maize consumption, 0.48% increase in household income and 0.24% increase in value of asset accumulation," with the highest improvements among the poorest farmers (Bezu et al. 2014). Improving crop diversity in Uganda was also associated with highest consumption improvements among the poorest households (Tesfaye and Tirivayi 2020).

In terms of indirect effects, there is no conclusive evidence that agricultural inputs alone result in

3 *The model assumes that the primary purpose of the anticipatory actions is to prevent losses due to drought. For example, early actions during a drought can prevent households from selling productive assets to finance food and essential requirements. Many actions such as providing drought-resistant seeds and tubers are geared to prevent higher losses during drought. However, during good states of economy, we assume there is no penalty for taking early actions. However, there is also no additional benefit from them other than the at-par monetary value. Similarly, in an extreme case when the losses are fully recovered through early actions, any additional action does not provide any incremental return.*

4 *The payment frequency of the AI product, then, is once in every 1/q years where q = Prob(I>Iatt).*

poverty alleviation or improved health (Hemming et al. 2018). Studies of Malawi's farm input subsidy program find that it does not seem to be increasing dietary diversity (Walls et al. 2023), and a lowered price of maize does not encourage dietary diversity among households that are already food insecure (Matita et al. 2023). However, people who used the farm subsidies to access legume seeds did have higher dietary diversity (Matita et al. 2022), so the provision of sweet potatoes and cassava in this anticipatory insurance program could help support dietary diversity. In terms of outcomes for children, farm subsidies and nutrition interventions have been shown to have only short-term effects on child health, such as improved weight-for-age in the moment, but do not affect long-term measures of malnutrition, such as height-for-age. When paired with maternal and post-infancy community nutrition and health programming, however, farm inputs can have longer-term effects (Mwale et al. 2022).

Taken together, the benefit-cost ratio of fertilizer and seed distribution in Malawi is likely to be greater than 1. A study of a Millenium Villages Project in Malawi found that the provision of seeds and fertilizer resulted in a benefit-cost ratio of 2.3, and an evaluation of the 2006–2007 farm subsidies estimated a range of direct benefit-cost ratios of 0.76–1.36, without considering indirect benefits (Arndt et al. 2016). Arndt et al. (2016) found that the overall benefits of these inputs are most sensitive to how we estimate the marginal returns to fertilizer use, and that the economy-wide benefit-cost ratio of fertilizer and seed subsidies in Malawi was estimated to be as high as 1.99 (with a production-based benefit-cost ratio of 1.06). However, under a scenario of low marginal returns to fertilizer use, the economy-wide benefit-cost ratio was as low as 0.77. Using official estimates of fertilizer response rates, the study found that the direct benefits relative to the costs were approximately equal (a ratio of approximately 1), but that the economy-wide benefit-cost ratio that takes into account indirect benefits was estimated to be 1.62. This difference was primarily due to the greater use of land for nonmaize cash crops, enabled by the improved maize seeds (Arndt et al. 2016).

While we might not assume the success of cash crops in a drought year during the ARC anticipatory insurance payout, the benefits of drought-resistant seeds might be highest in drought years, and therefore maintain a high benefit-cost ratio. The same study found that a rare 20-year return period drought would cause reductions of maize yields by one-third, while improved varieties could maintain high yields and sustain losses between 10 and 20% during the same conditions (Arndt et al. 2016).

Therefore, in this study, we will assume a range of plausible benefit-cost ratios between 1 and 2 for the economic analysis. We propose an impact evaluation plan that would enable assessment of the true benefits and costs after a pilot has happened.

Other Assumptions for Numerical Analysis

We make the following model assumptions for the economic analysis of the AI product. The country faces a 1-in-5-year drought risk, i.e., $p=0.20$. The country mirrors the risk preferences of its people, who have constant relative risk-averse preferences over wealth, with a relative risk aversion of 2.0. This means that it derives a utility of $u(w)=-1/w$ from a wealth level of w. The benefit-to-cost ratio of early actions, as discussed above, varies in the range of 1 to 2, i.e., $\beta \in [1,2]$. The premium loading is 35%, i.e., the AI product's premium is 1.35 times the actuarially fair price (the expected loss).[5]

We also make assumptions about the skill of forecast technology. Our measure of the forecast skill is the correlation between the occurrence of the drought and the triggering of the payment of the AI product (or the triggering of the anticipatory action) in our model. We let the correlation vary from 0.2 to 0.8, i.e., $\rho \in [0.2,0.8]$, which captures a reasonable range of the forecast skill. This approach is equivalent to making model assumptions about the correlation between the forecast and actual response cost of the drought.

Optimal Coverage Under the Anticipatory Insurance (AI) Product

The optimal AI coverage to purchase in a context depends on the basket of early actions and alternative financing mechanisms available to

5 *Premium loading is based on the model calculation for the AI product shared by ARC.*

decision-makers. Before we examine the optimal coverage under the AI product, we briefly discuss an extreme, but possible, case, when it is not beneficial to take forecast-based early actions, i.e., the benefit-cost ratio of the actions is less than 1.

The Assumptions of the Theory of Change Are Not Met, and Therefore the Benefit-Cost Ratio Is Less Than 1.

This scenario may unfold due to a combination of factors, even beyond those mentioned here. Premium defaults and other administrative-related delays or errors present a significant challenge, where individuals or entities fail to fulfill their financial or contractual obligations, disrupting the anticipated cash flow essential for success. Once a payout is triggered, timing and delays at every step of the implementation process can lead to misalignment between projected and actual outcomes. Relatedly, poor targeting systems have been identified as a significant barrier to taking timely action. Another point of caution arises from procurement issues, which may include challenges in sourcing necessary resources or services, hindering the ability to deliver aid to recipients. It is crucial to implement careful monitoring of the potential points of failure noted in the theory of change to mitigate adverse impacts on overall benefit.

In addition to the measurable factors, there could be unforeseen consequences related to policy and public interests. Walls et al. (2023) describe lessons learned from a farm input subsidy program in Malawi and mention gaps in policy implementation expectations compared to results, influence of policy and corporate actors, misalignments between intended outcomes and public interest or actual ability to meet those intended outcomes due to resource constraints, and unforeseen emerging trade-offs related to new program implementation as important considerations for intervention planning and implementation (Walls et al. 2023). In a systematic review on agricultural input subsidies for low- and middle-income countries, Hemming et al. (2018) found that fertilizer and seed subsidies are linked to elevated input use, higher agricultural yields, and increased farm household income, but their impact on poverty is inconclusive. They suggest there are, overall, positive effects on consumers and economic growth, but persisting concerns regarding subsidy inefficiency, bias, and susceptibility to corruption, with funding mechanisms, global input prices, and beneficiary targeting playing crucial roles in determining outcomes (Hemming et al. 2018). Both literature and qualitative interviews conducted for this study (see Table 2) support the need for careful monitoring of the program from initial forecasting through postdistribution to ensure positive benefits are realized.

Benefit-Cost Ratio of Early Actions Is Greater Than 1.

In this section, we assume that it is beneficial to take forecast-based early actions. We examine the optimal coverage under the AI product, focusing on the country's capacity to plan and self-finance early actions. We consider two scenarios:

1. Countries do not have the means to access forecasts or the capacity to take early actions in the absence of the AI product.
2. Countries have access to forecasts and can self-finance early actions even when the AI product is not available.

Scenario 1: Countries Do Not Have the Means to Access Forecasts or the Mechanisms to Take Early Actions in the Absence of the AI Product.

In this scenario, we assume that a country does not have access to any forecast-based anticipatory action mechanism. This means that a country will not be able to finance and execute the early actions unless the financing and capacity-building support are available through the AI product.

Figure 5 shows the optimal level of ceding ratio under this scenario for different values of basis risk, anticipatory action return period, premium loading, and benefit-to-cost ratio of early actions. The x-axis on each graph is the return period of the anticipatory action, i.e., 1/q. The y-axis on each graph is the ceding ratio. There are 16 panels based on different values of basis risk (i.e., correlation between the occurrence of drought and the triggering of the AI product payment) along the rows and benefit-to-cost ratio of early actions along the columns.[6] The solid and dashed black lines in the graph represent optimal ceding for the premium loadings of 0% and 35%, respectively.

The figure shows that when forecasts have high skill (e.g., the top row where basis risk is low) and premium loading zero, the optimal coverage of anticipatory action is the maximum level of action that is required to recover all the losses, i.e., l/β.[7] For example, when anticipatory actions provide a benefit of $1.25 for every $1 spent (the top-left panel), spending $l/1.25$ will result in a benefit of l, which is sufficient to cover the losses l. Since the y-axis shows the coverage as a fraction of loss, it is $1/1.25=0.8$. When either the premium loading is higher or the basis risk is higher, the optimal coverage is almost always lower than the maximum limit, unless the return period is very high. This suggests that if a country chooses to finance anticipatory actions with a lower return period (higher frequency), then the optimal decision is to choose a lower level of AI coverage (for financing the action) that may not recover all the losses. For example, in the first panel of the second row (β=1.25 and ρ=0.6), the optimal coverage is around 0.6 for a return period of 5 years, but nearly 0.8 for return period of more than 20 years.

When Does the Optimal AI Coverage Exceed Zero?

The primary insight from the figure is that the optimal level of ceding ratio is always above zero when a country cannot finance forecast-based early actions in the absence of the AI product. This means that in such a scenario, the AI product contributes to the welfare through its insurance-based financing as well as the early action capacity-building mechanism. The AI product is valuable to the country because (a) it provides funds to the country to take early action when response cost is forecast to be high, and (b) it enables the country to act on the forecast.

This suggests that even for the coverage of anticipatory action financing with a significantly lower return period of five years, the AI product will be valuable under reasonably unfavorable parameters—the bottom-left graph shows that the optimal ceding ratio is above zero for cases where the early actions provide a per-dollar return of 1.25 and the correlation between drought occurrence and AI product trigger is 0.20. However, it should be noted that both the insurance and the early action capacity building contribute to this value.

6 *In practice, the basis risk is determined by the skill of the forecast technology.*

7 *In our model, the return from anticipatory action is in the form of a reduction in losses during drought. However, there is neither an additional return nor a penalty once the losses are fully covered or during a good state (when there is no drought). So, the maximum spending on anticipatory action under any given scenario will be capped at l/β, the amount of action sufficient to recover all the losses.*

FIGURE 5. Optimal ceding ration uder AI: Assuming no self-funding for early action

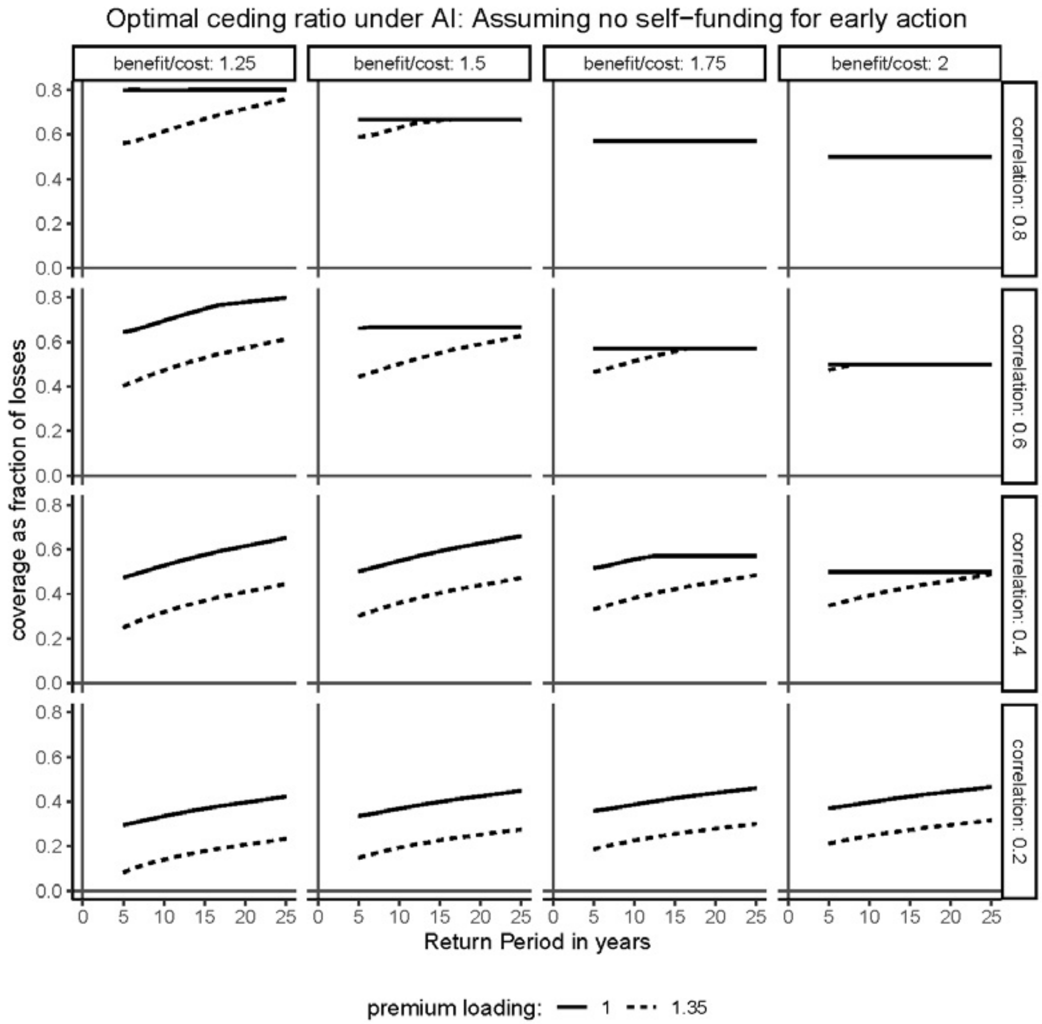


Figure 5. The figure plots the optimal ceding ratio (fraction of response cost to be covered) of the AI product for different values of basis risk, return period, premium loading, and benefit-to-cost ratio of early actions. The analysis assumes a scenario where the country does not self-finance the forecast-based early actions. The x-axis on each graph is the return period of the loss event covered. The y-axis on each graph is the ceding ratio. There are 16 panels based on different values of basis risk (i.e., correlation between the occurrence of drought and the triggering of the AI product payment) along the rows and benefit-to-cost ratio of early actions along the columns. The solid and dashed black lines in the graph represent optimal ceding for the premium loadings of 0% and 35%, respectively. The analysis assumes a relative risk aversion of 2 and a total response cost of 50% relative to the wealth of the country.

Scenario 2. Countries Have Access to Forecasts and Can Finance Early Actions Even When the AI Product Is Not Available.

Here, we assume that a country has access to forecasts and can self-finance anticipatory actions. This means that a country already has an early action mechanism in place and is financing and executing these early actions at some appropriate level before purchasing the AI product. In the scenario, the value proposition of the AI product is primarily through the insurance mechanism, i.e., its ability to provide insurance payout during the times when the adverse event is forecasted to occur.

Figure 6 shows the optimal level of ceding ratio under this scenario for different values of basis risk, return period, premium loading, and benefit-to-cost ratio of early actions. The x-axis on each graph is the return period of the loss event covered. The y-axis on each graph is the ceding ratio. There are 16 panels based on different values of basis risk (i.e., correlation between the occurrence of drought and the triggering of the AI product payment) along the rows and benefit-to-cost ratio of early actions along the columns. The solid and dashed black lines in the graph represent optimal ceding for the premium loadings of 0% and 25%, respectively. The solid red line shows the total investment in anticipatory action (self-funded plus AI funded). Since, in this scenario, countries can self-finance anticipatory action fully or partially, it would be optimal to invest in early loss-reducing actions as long as: (1) the benefit-to-cost ratio is greater than one; (2) there is funding available to invest in early actions; and (3) the potential losses are greater than the total benefit of early actions. We assume a fixed return on early actions. So, the optimal level of total anticipatory action is a level at which all losses are recovered. These results are also consistent with those in Anand (2022), which suggest that the overall level of anticipatory action does not depend on forecast skill (basis risk). Hence the red line is always flat and depends only on the benefit-to-cost ratio β.

When Does the Optimal AI Coverage Exceed Zero When Countries Can Self-Finance Early Action?

The primary insight from Figure 6 is that when counties already have access to a forecast-based early action mechanism and can self-finance these actions, purchasing anticipatory insurance is not always optimal. In fact, the optimal level of ceding ratio is greater than zero only when basis risk, premium loadings, or the benefit-to-cost ratio of early actions are below a certain level. The figure shows that as premium loading or basis risk increases, the proportion of early action financed by the AI product decreases for a given profile of the early actions. However, the figure also shows that optimal ceding decreases as the benefit-to-cost ratio of early actions increases. Although this does not seem intuitive at first, this decrease in optimal ceding follows from the decrease in total optimal investment in anticipatory action as the benefit-to-cost ratio increases. As we discuss earlier, the optimal demand for total investment in early action is proportional to 1/β. As the profile of early actions improves (i.e., β increases), countries need to invest less in early action, and hence there is less demand for the AI product coverage.

At a premium loading of 35%, i.e., a total premium of 135% of the actuarially fair pricing, the optimal ceding level under the AI product is zero or very small when both basis risk and benefit-to-cost ratio of actions are high. The figure shows that when correlation between drought occurrence and early action trigger is 0.2, then the optimal ceding is always zero. When the correlation is 0.4, the optimal ceding is above zero only for actions with benefit-cost ratio of less than 1.5.

This is because when countries can self-finance early action, it is not worth paying the premium loadings when basis risk is high. The potential premium payments are better used to finance early action—especially when these actions are highly effective.[8]

8 *We assume that any aid explicitly designated for financing the AI premium will still be given to the countries and directly allocated as budget funds if countries opt not to purchase the AI product.*

FIGURE 6. Optimal ceding ration under AI: Assuming self-funding for early action

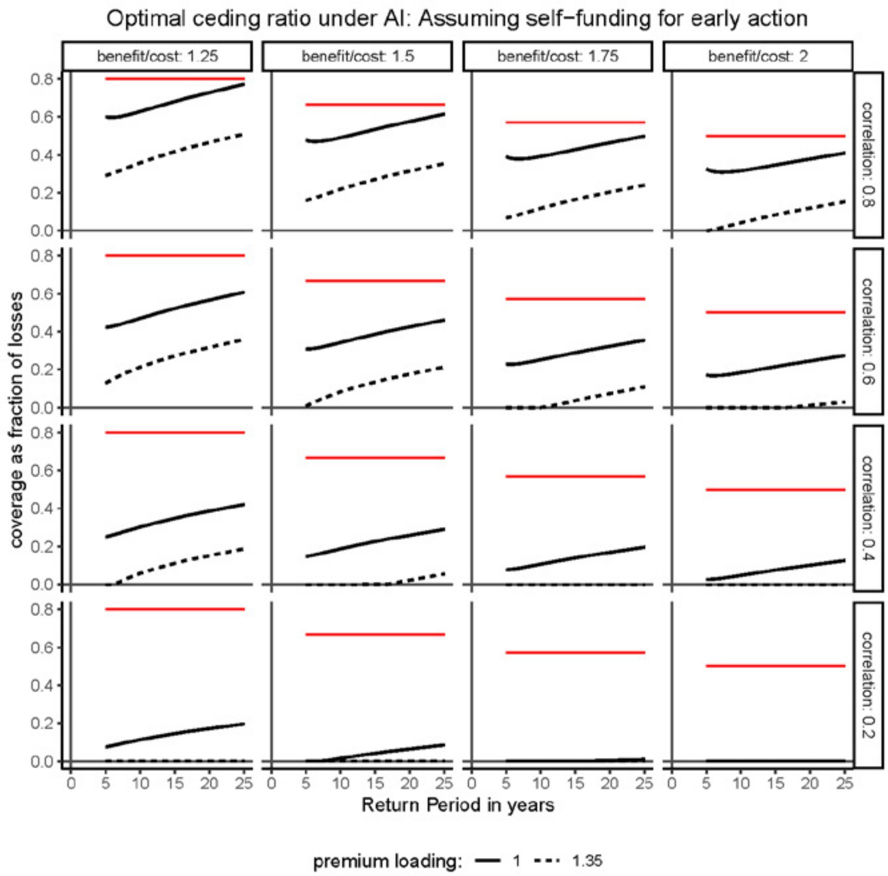


Figure 6. The figure plots the optimal ceding ratio (fraction of response cost to be covered) of the AI product for different values of basis risk, return period, premium loading, and benefit-to-cost ratio of early actions. The analysis assumes a scenario where the country has access to forecasts and can self-finance an optimal level of forecast-based early actions in the absence of the AI product. The x-axis on each graph is the return period of the loss event covered. The y-axis on each graph is the ceding ratio. There are 16 panels based on different values of basis risk (i.e., correlation between the occurrence of drought and the triggering of the AI product payments) along the rows and benefit-to-cost ratio of early actions along the columns. The solid and dashed black lines in the graph represent optimal ceding for the premium loadings of 0% and 35%, respectively. The solid red line shows the total investment in anticipatory action (self-funded plus AI funded). The analysis assumes a relative risk aversion of 2 and a total response cost of 50% relative to the wealth of the country.

Welfare Analysis

In this section, we compare the welfare of the country under different scenarios to examine how better off or worse off a particular risk financing strategy is compared to a counterfactual. We measure the welfare as the certainty equivalent wealth—the amount of certain wealth that would make the country indifferent between having the certain wealth or having the risk of loss event managed by the risk financing strategy.

For this analysis, we continue with the two counterfactual scenarios from the previous section for the risk financing mechanism of the country, i.e., either the country can take forecast-based early action in the absence of the AI product, or the country cannot take early action unless the AI product provides insurance payout and capacity-building support. Additionally, we examine two types of offerings from ARC. The first is the proposed AI product that provides a forecast-based insurance payout and capacity-building support. The second alternative offering is to provide only the forecast and capacity-building support for early action, i.e., there is no insurance mechanism. The two counterfactual scenarios for the country and the two potential offerings by the ARC result in four possible scenarios. We represent these four possible scenarios in Table 3 below.

TABLE 3. Different scenarios based on product offered by ARC and alternative counterfactuals (financing mechanisms) available to countries

	Counterfactual 1 (CF1) Country has neither the capacity nor the access to forecasts for early actions: No early action being taken currently	**Counterfactual 2 (CF2)** Country has both the access to forecasts and the capacity for early actions: Forecast-based early action is implemented at some level.
Offer 1 ARC offers the current AI product.	**Scenario A** Country funds early action using the AI payout only.	**Scenario B** Country augments its early action financing with the AI payout.
Offer 2 ARC offers forecast and capacity-building support (but no insurance).	**Scenario C** Country self-finances forecast-based early actions.	**Scenario D** Country continues to self-finance forecast-based early action.

In this analysis, we examine the following questions:

1. What is the additional welfare offered by the AI product (offer 1) to a country where there is no early action taken currently because it has neither the capacity nor the access to forecasts (i.e., scenario A with counterfactual 1)?
2. What is the additional welfare offered by the AI product (offer 1) to a country in a scenario where it has both the access to forecasts and the capacity for early actions, with forecast-based early action being currently implemented (i.e., scenario B with counterfactual 2)?
3. What is the additional welfare offered by the capacity-building support (offer 2) to a country under scenario C with counterfactual 1 (i.e., where there is no early action taken currently because it has neither the capacity nor the access to forecasts)?
4. What is the additional welfare offered by the AI product (offer 1) compared to capacity-building support (offer 2) to a country under counterfactual 1?

Welfare Gains From the AI Product

Scenario A and B: Welfare Gain From the AI Product Based on a Country's Ability to Self-Finance Early Actions

In this section, we examine the additional welfare offered by the AI product to a country under two different counterfactuals: CF1 where there is no early action taken currently because the country has neither the capacity nor the access to forecasts; CF2 where the country has both the access to forecasts and the capacity for early actions, and is currently financing early actions at an optimal level without insurance. Most countries are likely to be somewhere between the two counterfactuals. Under the first counterfactual, the value of AI product comes from its ability to provide forecast information, early action capacity-building support, and insurance-based financing. Whereas under the second counterfactual, the value of AI product comes only from its ability to provide insurance-based financing.

Figure 7 plots the welfare gains (as a fraction of the baseline welfare) from the AI product under the two counterfactuals, for different values of basis risk, return period, premium loading, and benefit-to-cost ratio of early actions. The solid and dashed lines in the graph correspond to counterfactual 1 and 2, respectively. The analysis assumes a baseline scenario where the country does not self-finance the forecast-based early actions under CF1, whereas the country self-finances the forecast-based early actions under CF2. The x-axis on each graph is the return period of the AI product payment. The y-axis on each graph is the welfare gain as a fraction of the baseline welfare. We assume the premium loadings of 35%.

There are three key results. First, the figure shows that the AI product is more valuable when a country cannot self-finance early actions (either the country lacks access to forecasts or it lacks the capacity to take early actions). The solid line (welfare gain from AI when early actions cannot be self-financed) is always above the dashed line (welfare gain from AI when early actions can be self-financed), irrespective of the basis risk, return period of insurance payout, or the benefit-to-cost ratio of early actions. Second, when countries can self-finance forecast-based early actions, the welfare gain from AI is quite small, even when it is beneficial. Together, these two results suggest that the primary benefit of the AI product stems from its ability to allow the countries to access forecast information and build early action capacity. When a country already has these two advantages, the additional benefit of insurance-based financing from the AI product is only marginal. Third, the figure shows that the solid lines slope downward, whereas the dashed lines slope upward (though it is not apparent due to the smaller scale). This suggests that when a country cannot self-finance early action, the benefit from AI increases with the frequency of AI payout, i.e., the shorter the return period, the greater the welfare gain from the AI product. Whereas when a country can self-finance early action, the additional benefit from AI product decreases with the frequency of AI product, i.e., the longer the return period of AI payout, the greater the welfare gain. This is because when early action is conditional on AI payout (CF1), it is welfare improving to receive a frequent payout because early action benefits outweigh the premium costs of insurance.

Should ARC Offer Insurance or Capacity Building?

Figure 7, along with the previous discussion, shows that the primary benefit of the AI product comes from its ability to provide forecast information and early action capacity-building support to a country. However, the capacity-building support as part of the current AI product may not enable the country to fully utilize the benefits of forecast-based early action. For example, if the operating plans for early action are tied to AI financing, then a country may not scale up early action using its own funds (e.g., using budget allocations). So, to maximize a country's benefit from forecast-based early actions, capacity-building support and operating plans should extend beyond relying solely on anticipatory insurance financing.[9] In this section, we compare the welfare gain of two product offerings from ARC as mentioned in Table 3: (1) the current AI product that ties the early action operating plans to AI financing; and (2) a product that offers forecast information and early action capacity-building support, but no insurance financing. Note that both the products will enable a country to take forecast-based early actions. However, the first product will let the country finance these actions using AI payouts only, whereas the second product builds the capacity and allows the country to self-finance early actions (relying solely on their income).

9 *Although we assume that the current AI product allows early action to be funded by the insurance financing only, in practice once the early action capacity is developed, a country can also self-finance early action. However, it may be costly for countries to extend their operating plans, which are tied to AI financing, in the short term.*

FIGURE 7. Scenario A vs B: Welfare gain from AI product

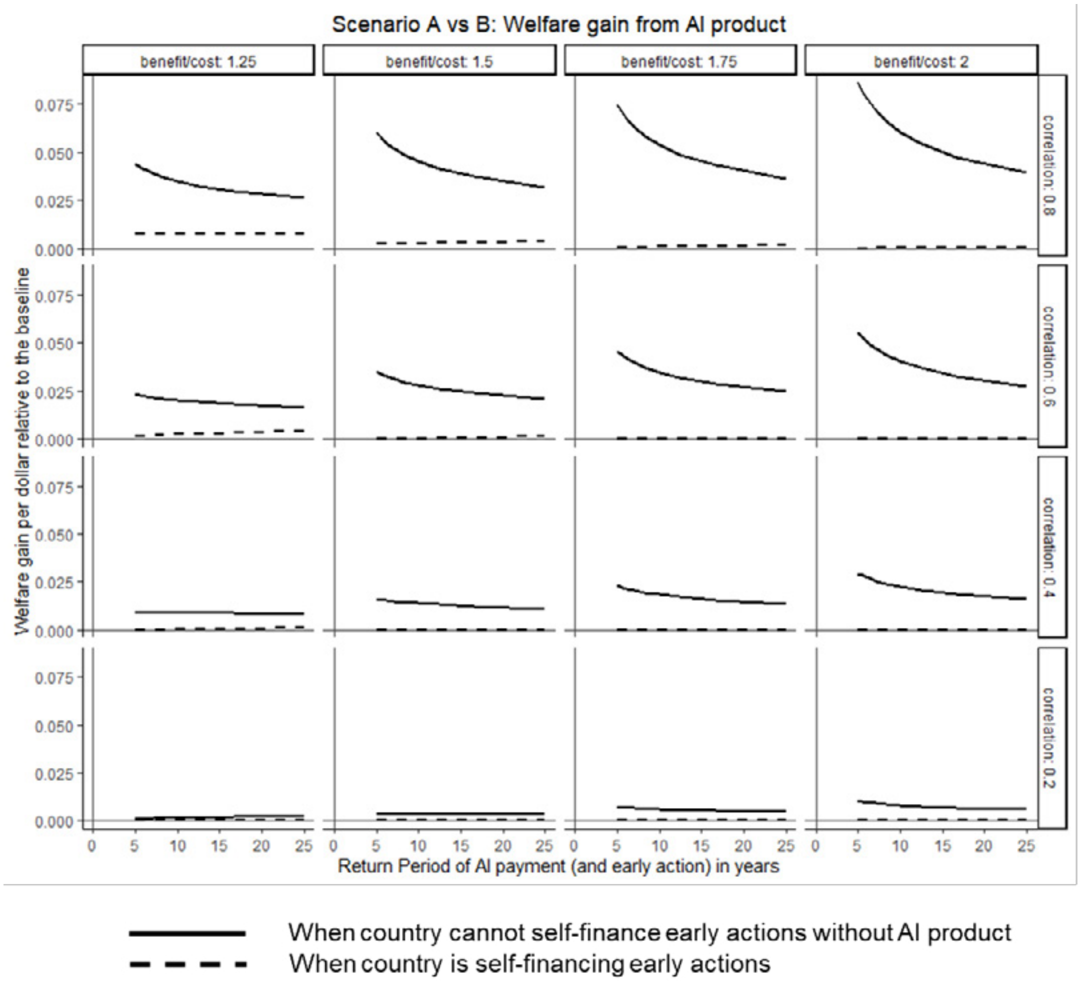


Figure 7. The figure plots the welfare gains (as a fraction of the baseline welfare) from the AI product under the two counterfactuals, for different values of basis risk, return period, premium loading, and benefit-to-cost ratio of early actions. The solid line in the graph corresponds to counterfactual 1 that assumes a baseline scenario where the country does not self-finance the forecast-based early actions. The dashed line in the graph corresponds to counterfactual 2 that assumes a baseline scenario where the country self-finances the forecast-based early actions. The x-axis on each graph is the return period of the loss event covered. The y-axis on each graph is the welfare gain as a fraction of the baseline welfare. There are 16 panels based on different values of basis risk (i.e., correlation between the occurrence of drought and the triggering of the AI product payment) along the rows and benefit-to-cost ratio of early actions along the columns. We assume the premium loadings of 35% for the AI product. The analysis assumes a relative risk aversion of 2 and a total response cost of 50% relative to the wealth of the country.

Figure 8 plots the welfare gains (as a fraction of the baseline welfare) from the two product offerings, the current AI product (solid line) and a pure capacity-building support (dashed line) for a country that cannot self-finance early action due to the lack of capacity or access to forecasts. The welfare gains are plotted for different values of basis risk, return period, premium loading, and benefit-to-cost ratio of early actions. The analysis assumes a baseline scenario where the country takes no forecast-based early actions. The x-axis on each graph is the return period of the AI product payment or the early actions financing. The y-axis on each graph is the welfare gain as a fraction of the baseline welfare. We assume the premium loadings of 35% for the AI product.

The figure shows that in general a capacity-building support is more beneficial than the current AI product. Specifically, the solid line (representing welfare gains from the AI product) is positioned below the dashed line (indicating welfare gains from pure capacity building) under most conditions. In fact, the gains from the AI product surpass those from capacity-building support only in a scenario with a low benefit-to-cost ratio and high correlation (low basis risk). This is due to the additional value addition from insurance financing when early actions are costlier relative to their benefits and the forecast's accuracy is high. In all other scenarios, insurance financing is less valuable than capacity-building support that allows the country to self-finance early action (and not just rely on AI payouts).

The figure also shows that the relative benefit of pure capacity-building support over the current AI product increases with an increase in basis risk and early action frequency. Under moderately low basis risk, when early action (and AI payout) is triggered with a longer return period, both products offer similar welfare gain. When the basis risk is higher, capacity-building support is always more beneficial.

Note that all of these points assume that capacity building within the country is effective.

FIGURE 8. Scenario A vs C: Welfare gain from AI vs FbF Capacity: No self-funding for early action

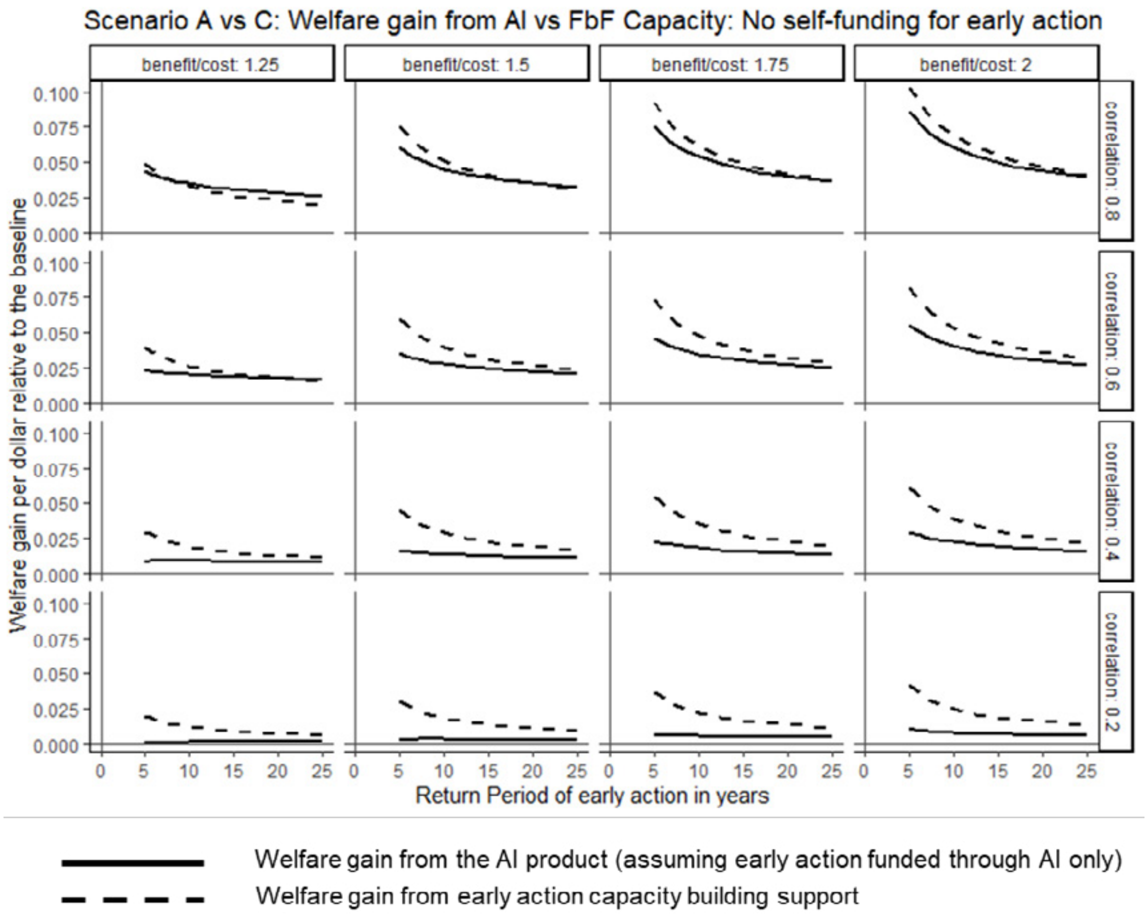


Figure 8. The figure plots the welfare gain from the AI product (solid line) relative to the forecast-based financing (FbF) building support (dashed line), as a fraction of the baseline welfare, for different values of basis risk, return period, premium loading, and benefit-to-cost ratio of early actions. The analysis assumes a baseline scenario where the country does not self-finance forecast-based early actions in the absence of the AI product or the FbF capacity-building support. The x-axis on each graph is the return period of the AI product payment or the early actions financing. The y-axis on each graph is the welfare gain as a fraction of the baseline welfare. There are 16 panels based on different values of basis risk (i.e., correlation between the occurrence of drought and the triggering of the AI product payments) along the rows and benefit-to-cost ratio of early actions along the columns. We assume the premium loadings of 35% for the AI product. The analysis assumes a relative risk aversion of 2 and a total response cost of 50% relative to the wealth of the country.

Key Inferences From the Economic Analysis

The demand for the current AI product is always positive when a country cannot self-finance early action, due to the lack of capacity or access to forecasts. However, when the country has access to a forecast-based early action mechanism and can self-finance these actions, purchasing anticipatory insurance is not always optimal. In fact, the optimal demand for AI is positive only when basis risk, premium loadings, or the benefit-to-cost ratio of early actions are below a certain level.

A country faces two trade-offs when it has access to both self-financed early action and the AI product. The first trade-off is whether to finance early action or use funds to recover losses after the disaster. This trade-off worsens when early action benefits are smaller compared to cost. As countries spend more dollars on early action now, the marginal cost of action is higher. The second trade-off is about AI, which is whether to pay the premium for insurance benefits, but also risk having less wealth when disaster occurs, but insurance doesn't pay. This trade-off worsens when the basis risk is high. However, when basis risk is low and the marginal cost of early action is higher (e.g., when benefits-to-cost ratio is lower), insurance can allow countries to finance early action while saving some of their current wealth to aid recovery later. Hence, the primary benefit of the insurance financing mechanism in the AI product is most salient when early actions benefits are smaller compared to their costs and when basis risk is low. In such situations, insurance enables countries to finance early actions that could not have been self-financed.

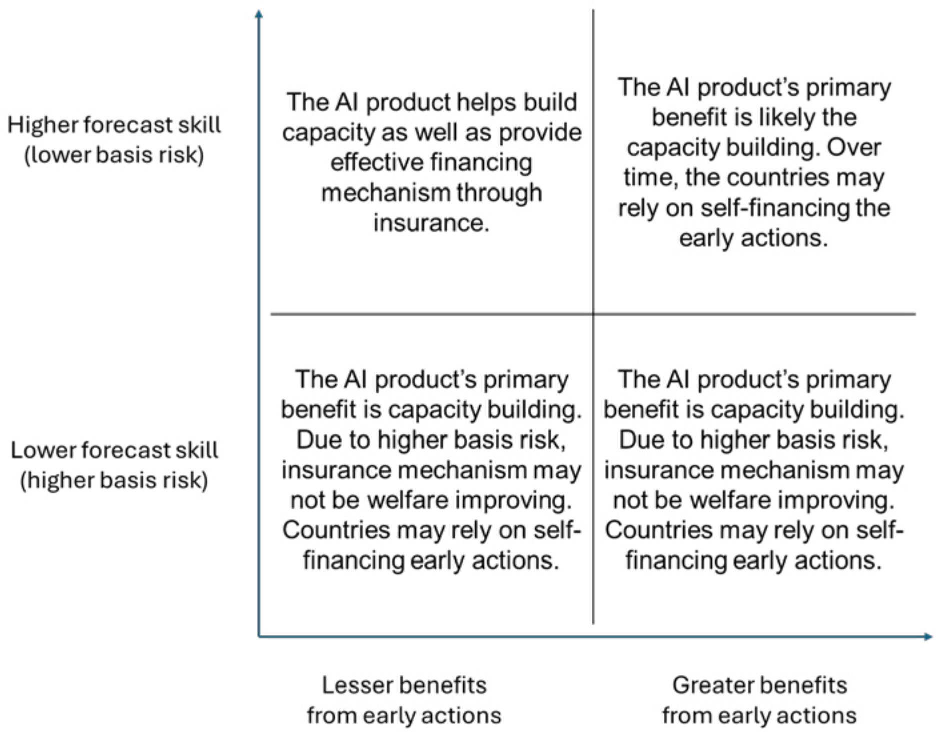
In most other scenarios, the primary benefit of the AI product comes from its ability to build early action capacity and provide forecast information. So, the choice between the current AI product and pure capacity-building support is likely to be based on the level of basis risk and the profile of early actions. Table 4 summarizes the results of our analysis and highlights the recommended strategy.

TABLE 4. Which product or service is preferred for a country that does not have early capacity: Anticipatory insurance (AI) or capacity-building support (CBS)?

	BENEFIT/COST: 1.25		BENEFIT/COST: 1.5		BENEFIT/COST: 1.75		BENEFIT/COST: 2	
CORRELATION: 0.8	Both	AI	CBS	Both	CBS	Both	CBS	Both
CORRELATION: 0.6	CBS	Both	CBS	CBS	CBS	CBS	CBS	CBS
CORRELATION: 0.4	CBS	CBS	CBS	CBS	CBS	CBS	CBS	CBS
CORRELATION: 0.2	CBS	CBS	CBS	CBS	CBS	CBS	CBS	CBS
RETURN PERIOD →	Shorter	Longer	Shorter	Longer	Shorter	Longer	Shorter	Longer

Overall, these results suggest that to mitigate risk using forecast-based early actions, capacity-building support and access to forecast may be the primary requirements, while the financing through the insurance mechanism in the AI product provides the secondary benefits. However, for countries that may need to cover a significant gap from having little or no capacity to be able to take effective early actions, it may be challenging to reallocate resources from other priorities to capacity building for early actions. The AI product's pilot program provides an opportunity to help the countries' policymakers and other stakeholders to commit to developing the necessary infrastructure and processes. Once a country has developed the institutional and operational capacity to take early actions, it can choose the optimal source of financing for early actions based on the available forecast skill and early actions. Figure 9 below summarizes the primary benefit of the AI product for a country that lacks the capacity for early action. Our analysis suggests that ARC may need to first evaluate the current state of early action capacity of a country as well as the quality of early actions and forecasts available to the country. This evaluation can inform the relative benefits of the capacity-building and AI product over the short and long term.

FIGURE 9. What is the primary benefit of the AI product for a country that does not have capacity of early action?



Key Limitations of the Economic Analysis

In this study, we employ two extreme counterfactual scenarios for analysis: first, countries equipped with both the necessary forecasts and capacity, and second, countries lacking either element. However, it's important to note that numerous countries fall within a spectrum between these extremes. Many nations possess social safety net or welfare programs with extensive last-mile coverage yet lack integration with a predictive trigger mechanism. The potential expenses associated with transitioning an existing program into an anticipatory system may differ significantly from the costs of initiating one from scratch. Similarly, all countries will have limitations to their ability to finance anticipatory action (AA). Therefore, evaluating the relative costs and benefits of each approach in each context becomes important for informed decision-making.

An essential aspect influencing the benefit-cost ratio is the potential improvement in forecasting abilities in the future. Advancements in technology, data availability, and modeling techniques such as the inclusion of seasonal forecasts in ARV models may lead to more accurate and precise predictions of extreme events. These improvements could significantly alter the perceived benefits of implementing AI systems for risk management. Relatedly, utilizing a constant value for model performance may oversimplify reality. It is common for models to excel in identifying the most extreme years, leading to higher accuracy as the return period extends.

Plan for Monitoring and Evaluation

The purpose of this monitoring and evaluation (M&E) plan is to describe how implementing partners will monitor and evaluate the implementation of ARC's Anticipatory Insurance Program. This plan proposes indicators against each of the expected results of the program using the theory of change (ToC) in Figures 3 and 4. The ToC shows each assumption, denoted by purple boxes. Each assumption is a potential point of failure throughout the AI implementation process. The following is a plan for monitoring and evaluating as per the theory of change to estimate the realized costs and benefits when the product is piloted. This plan also describes the processes that will be used to perform M&E throughout the life of the program. Some of the tasks described may, in practice, be categorized as project management, but are included because these tasks are still viewed as critical for the success of the program.

Monitoring

During the implementation of the program, it is critical to continuously check the ongoing status of the program in comparison to the implementation plan by tracking actual versus desired outputs. In the context of AI, we consider the following questions, identified through the assumptions on the ToC:

- Was the forecast accurate?
- Were funds disbursed to governments according to schedule?
- Was targeting timely and efficient?
- Was the agency able to procure all inputs necessary to complete the intervention?
- Was aid disbursed to recipients according to schedule?
- Are the inputs viable for cultivation?
- Are farmers using the interventions as intended?
- Does the intervention reduce the cycle of humanitarian aid in the long term?

The monitoring and evaluation plan is pivotal for overseeing the implementation process and pinpointing operational risks that could hinder the program's progress and timely completion. It requires comprehensive documentation, prioritizing the prompt resolution of identified concerns instead of postponing them to the following year. Determining the monitored implementation activities should be a joint effort between the implementation and M&E teams.

Continuous assessments during program implementation involve comparing its current status to the planned framework, ensuring the program's alignment with its predefined goals while highlighting operational risks that may affect its progress. Clearly defining the scope of monitoring—what is included and what is excluded—is vital.

This monitoring approach offers diverse benefits, encompassing the assurance of plan adherence, identification of potential risks causing operational delays, and gauging the generalizability of the program's outcomes.

Effective monitoring should exhibit specific attributes: credibility through high-quality, reliable data collection; actionability at the program's inception to rectify issues; responsibility by ensuring the benefits of data collection outweigh associated costs and minimize respondent burden; and transportability, enabling the insights gained to be applicable to other similar programs, enhancing broader usability. See table 5.

TABLE 5. Mock-up of the monitoring process*

What decision?	What types of data?	How will it be collected?	Who will collect the data?	What method will be used to make sense of the data?	Who will use the monitoring information?	Who will make sure the system works?
Targeting criteria	Updating of targeting criteria based on community needs	During needs assessment surveys and focus group discussions (FGD)s	Program coordinators and enumerators	Excel and pivot tables	Evaluation team	ARC program team and governments
Availability of dataset	Compilation of ARV	Reports from the ARC team	Program analyst	ARV	Government Evaluation team	ARC program team
Tracking timely transfer of funds from ARC to government Tracking timely transfer to aid from government to farmer	% of funds that got transferred from ARC to the government Average time taken for transfer of funds from ARC to government then from government to farmer	$ value of funds transferred Number of days taken for the end-to-end transfer of fund	Program head	Planned vs. actual futures	Government, program implementation head, OCHA, future donors Evaluation team	Program implementation team
Completion of vulnerability assessment of affected households	# of district and village-level targeting criteria established # of HH-targeting criteria established	Through interviews and FGDs from program implementation teams	Monitoring team	Excel	Government, program implementation head, OCHA, future donors Evaluation team	Monitoring team

** Table 5 is not intended to be comprehensive. A full monitoring plan should be co-developed with ARC.*

TABLE 5. Continued

What decision?	What types of data?	How will it be collected?	Who will collect the data?	What method will be used to make sense of the data?	Who will use the monitoring information?	Who will make sure the system works?
Have the recipient farmers received the complete intervention?	# of recipient households who received the intervention # of transfers made to each household Type of intervention received Frequency of intervention	Surveys	Monitoring team	Excel	Program implementation head, OCHA, future donors Evaluation team	Monitoring team
Have the farmers utilized the intervention provided? How have farmers utilized the intervention provided?	# of farmers who have used the agricultural inputs # of farmers who have "used" the livestock # of farmers who have spent the cash Use of intervention	Surveys	Monitoring team	Excel	Program implementation head, OCHA, future donors Evaluation team	Monitoring team
What is the opinion of the farmers of the intervention? What were the positive benefits of the intervention? What were the negative consequences of the intervention?	Timing of intervention Relevance of intervention Benefits and costs of the intervention from the farmer perspective	Surveys; FGDs	Monitoring team	Excel	Program implementation head, OCHA, future donors Evaluation team	Monitoring team

Evaluation

The evaluation component within the monitoring and evaluation plan serves the purpose of assessing the efficacy, impact, and benefit-cost analysis of ARC's Anticipatory Insurance Program. This evaluation is designed to utilize indicators aligned with the expected outcomes delineated in Figures 3 and 4 of the theory of change (ToC). The ToC highlights various assumptions, each represented by purple boxes, indicating potential failure points in the implementation of the ARC Anticipatory Insurance Program.

The intent of this evaluation is to estimate the realized costs and benefits during the piloting of the program. This evaluation plan outlines a systematic process to continuously monitor and evaluate the initiative throughout its lifecycle.

Evaluation Objectives

The focus of the evaluation process is to meticulously assess the outcomes against the intended goals of the ARC Anticipatory Insurance Program. Specifically, the evaluation aims to address critical questions pertaining to the validity of assumptions identified in the ToC:

- Accuracy of the forecast in predicting risks.
- Timely disbursement of funds to governments as per schedule.
- Efficiency and punctuality in the targeting process.
- Procurement of all necessary inputs for intervention completion by the agency.
- Scheduled and effective aid disbursement to recipients.
- Viability of the inputs for cultivation.
- Compliance of farmers in utilizing the interventions as intended.
- Long-term impact in reducing the cycle of humanitarian aid.

The evaluation methodology and process are structured to determine the overall effectiveness, efficiency, and impact of the program, specifically focusing on these critical aspects identified within the ToC. It seeks to gauge not only the immediate outcomes but also the sustainability and transformative potential of the ARC Anticipatory Insurance Program.

Mechanism of Evaluation

The end-to-end process of evaluation involves a comprehensive and systematic analysis that encompasses data collection, quantitative and qualitative assessments, and interpretation. The evaluation will employ various data sources, including but not limited to financial records, program reports, stakeholder interviews, field observations, and beneficiary surveys. The synthesis and analysis of this collected data will form the basis for assessing the program's performance against its objectives.

This evaluation mechanism is designed to provide a robust and comprehensive understanding of the program's impact, strengths, weaknesses, and potential areas for improvement. By integrating these insights, the evaluation aims to inform and guide the ongoing adaptation and enhancement of the ARC Anticipatory Insurance Program. See table 6.

TABLE 6. Mock-up of the evaluation process*

Objective

Tie up the end objective of the evaluation with the outcomes of the terms of reference.

Understand the impact of the ARC program on the livelihood of farmers who received the intervention and on the resilience of farmers.

TOOLS	INDICATORS	TARGET GROUP/ PARTICIPANTS	MECHANISM	TIMING
Quantitative	Livelihood Coping Strategy Index (LCIS) Food Consumption Score (FCS) Reduced Coping Strategy Index (rSCI) Food Expenditure Share (FES) Consolidated Approach for Reporting Indicators of Food Security (CARI) Demographic indicators Women's dietary diversity	Farmers who received the intervention Farmers who did not receive the intervention Specific attention may be given to the female perspective.	Nonexperimental methodologies like differences-in-differences (DID) or propensity score matching; sampling strategy that has adequate statistical power to ensure the validity of the results	Baseline data: Before the implementation of the program Endline data: Four months after the implementation of the program
Qualitative	Questions on the effectiveness of program implementation: Organisation for Economic Co-operation and Development's Development Assistance Committee (OECD's DAC) framework Questions on perceptions of relevance, timeliness, and impact of interventions	Recipient farmers, program implementation teams, relevant government authorities, and other individuals closely linked with program implementation Women-specific focus groups should be held.	In-detail FGDs, key informant interviews (KIIs), semistructured interviews with recipients; OECD's DAC framework	Baseline data: Before the implementation of the program Endline data: Four months after the implementation of the program

* *Table 6 is not intended to be comprehensive. A full evaluation plan should be co-developed with ARC.*

Notably, the tools offered in this report would be catered to the specific contexts for each payout. For example, to ensure a more inclusive and effective approach, it is imperative to integrate indicators such as women's dietary diversity (WDD) and establish women-specific focus groups within the evaluation framework, especially in areas where land ownership is dominated by men, but the workforce is propelled by women. By doing so, we not only acknowledge the disproportionate burdens faced by women but also pave the way for more equitable and sustainable development outcomes.

METHODOLOGY

The research process was broken into three major work packages that complemented one another: 1) the development of the theory of change; 2) the economic analysis; and 3) the plan for impact evaluation. We began by carrying out a comprehensive literature review of approximately 50 documents provided by ARC. The review included a coding strategy that involved categorizing and tagging each document with one or more of the following tags: context, evaluation, contingency planning, transfer parameters, financing strategy, resource mobilization, payout, response costs, African RiskView, data, risk modeling, implementation, scaling, social welfare, and evaluation. The documents provided included technical reports, policy documents, contingency plans, insurance agreements, risk assessments, and other related materials. The review of the documents by the research team laid the foundation for more in-depth analysis and comprehension. This deep dive into ARC materials was complemented by additional scientific literature review to provide context and/or clarification. These documents were compiled and tagged in an Excel database for reference throughout the project.

Once a foundational understanding of the product was developed, an initial theory of change (ToC) for the AI product was drafted to outline the assumptions underlying the costs and benefits related to the product. This draft was circulated among select stakeholders for initial review. The team then traveled to participate in ARC workshops held in Malawi and Zambia, where the ToC, along with other project elements, was presented for additional feedback.

Conversations with workshop participants allowed for real-time validation of assumptions, clarification of concepts, identification of potential gaps in understanding, and exploration of emerging themes. The culmination of insights gained during the workshops better equipped the research team to contextualize and analyze literature, interview responses, and data.

Before, during, and following the workshops, a snowball method was used to recruit 10 participants for in-depth, one-on-one interviews. Individualized question guides for the in-depth semistructured interviews were formulated to address knowledge gaps from the document review process and to gain valuable insights and perspectives from stakeholders. More specifically, the interviews aimed to capture a holistic understanding of the program's associated assumptions, challenges, successes, and potential future directions.

Topics included the design and implementation of the insurance product, contingency planning, risk assessment, collaboration with stakeholders, challenges faced, decision-making processes, and the alignment of the project with broader goals. Among the interview participants were government officials, ARC representatives, UN representatives, and a farmer.

The ToC was revised to visualize the flow of the processes that lead to a desired outcome of reduced humanitarian impact. Input from interview workshop insights and interview follow-ups were integrated into the ToC. A number of interviews validated existing assumptions, in which case no changes were made.

The primary objective of the economic analysis is to assess the situations under which the anticipatory insurance mechanism is likely to have financial and economic viability and whether it represents a sustainable solution for reducing the humanitarian impact of climate-related disasters in Malawi and Zambia.

To do this, we used secondary literature to identify plausible benefit-cost ratios that accord with the theory of change and interview results. We include both the ratio assuming only direct benefits from agriculture and also the ration assuming indirect benefits from reduced negative coping strategies.

Based on this range of plausible benefit-cost ratios, we design three scenarios and calculate the outcomes of each scenario. The scenarios are as follows:

1. The assumptions of the theory of change are not met, and therefore the benefit-cost ratio is less than 1.
2. Countries do not have the means to access forecasts or the mechanisms to take early actions in the absence of the AI product.
3. Countries have access to forecasts and can finance early actions even when the AI product is not available.

For scenarios 2 and 3, we estimate the optimal ceding ratio and welfare benefits under a range of plausible benefit-cost ratios.

Finally, we outline a plan for an impact evaluation that would enable people to more accurately estimate the costs and benefits after a pilot activation of the anticipatory insurance mechanism.

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APPENDIX

Economic analysis results with lower response cost assumption, i.e., l=0.25w

When we assume a lower response cost, the advantage of the insurance financing mechanism of the AI product is relatively lower. Note that the optimum action is to self-finance and rely on insurance when self-financing becomes too costly. This is likely true when response cost is higher. When response cost is lower, the optimal coverage from AI is also lower. This is what we observe in all the results below, which are replicated for a lower response cost, i.e., l=0.25w.

FIGURE 10. Optimal ceding ratio under AI: Assuming no self-funding for early action

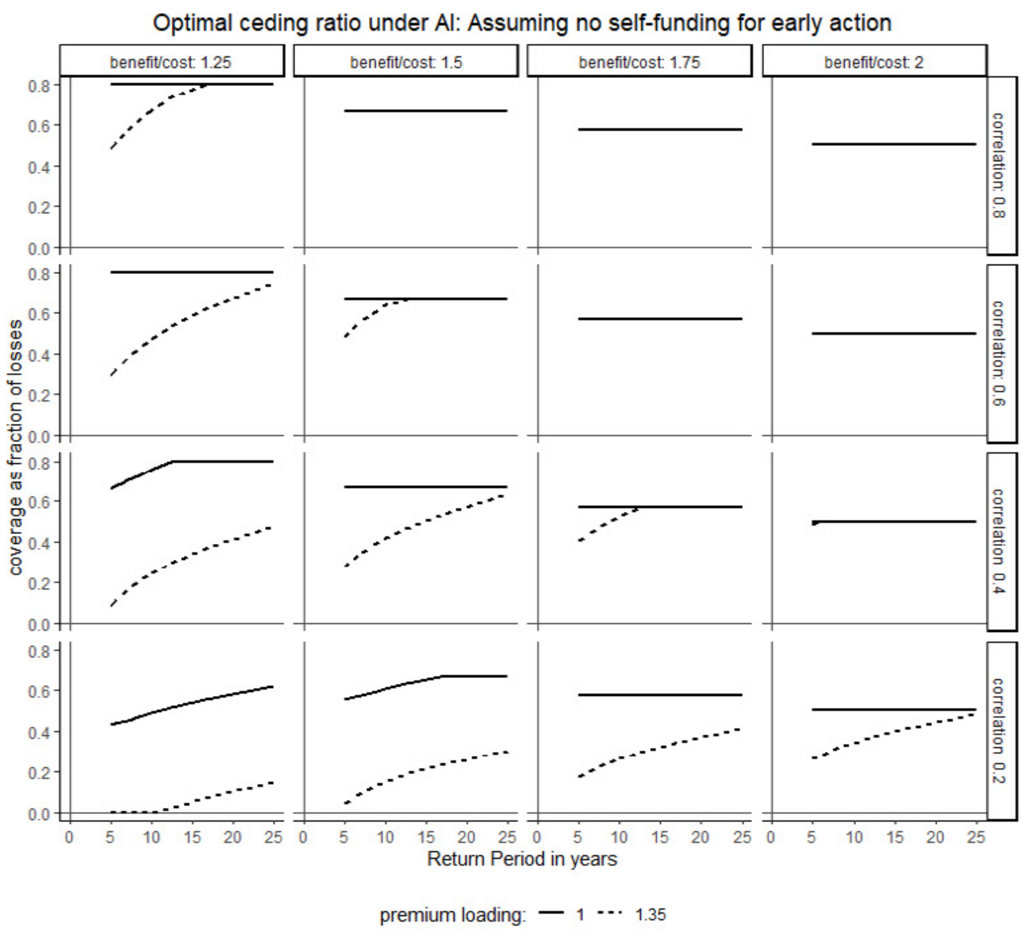

Figure 10. The figure plots the optimal ceding ratio (fraction of response cost to be covered) of the AI product for different values of basis risk, return period, premium loading, and benefit-to-cost ratio of early actions. The analysis assumes a scenario where the country does not self-finance the forecast-based early actions. The x-axis on each graph is the return period of the loss event covered. The y-axis on each graph is the ceding ratio. There are 16 panels based on different values of basis risk (i.e., correlation between the occurrence of drought and the triggering of the AI product payment) along the rows and benefit-to-cost ratio of early actions along the columns. The solid and dashed black lines in the graph represent optimal ceding for the premium loadings of 0% and 35%, respectively. The analysis assumes a relative risk aversion of 2 and a total response cost of 25% relative to the wealth of the country.

FIGURE 11. Optimal ceding ratio under AI: Assuming self-funding for early action

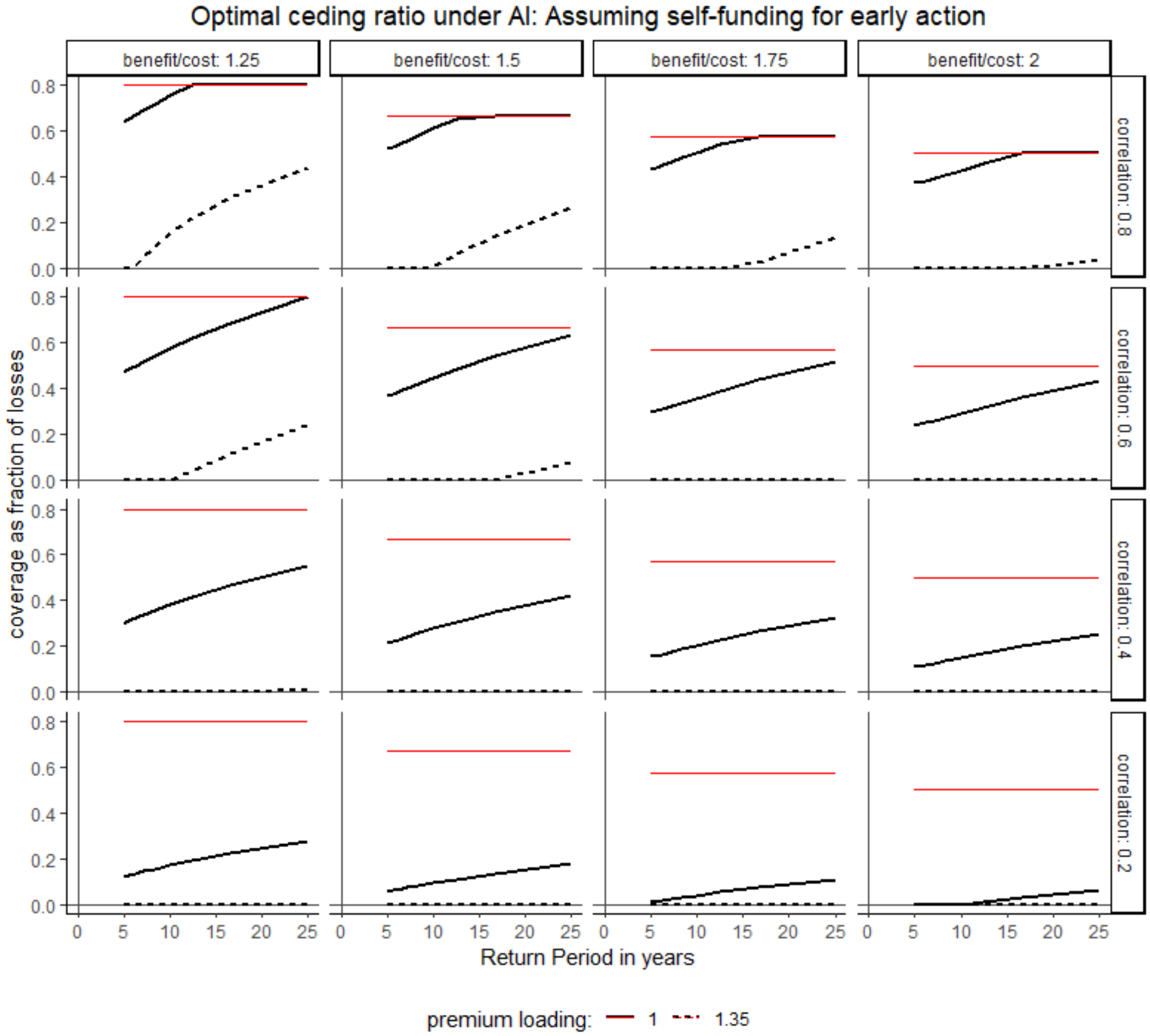

Figure 11. The figure plots the optimal ceding ratio (fraction of response cost to be covered) of the AI product for different values of basis risk, return period, premium loading, and benefit-to-cost ratio of early actions. The analysis assumes a scenario where the country has access to forecasts and can self-finance an optimal level of forecast-based early actions in the absence of the AI product. The x-axis on each graph is the return period of the loss event covered. The y-axis on each graph is the ceding ratio. There are 16 panels based on different values of basis risk (i.e., correlation between the occurrence of drought and the triggering of the AI product payments) along the rows and benefit-to-cost ratio of early actions along the columns. The solid and dashed black lines in the graph represent optimal ceding for the premium loadings of 0% and 35%, respectively. The solid red line shows the total investment in anticipatory action (self-funded plus AI funded). The analysis assumes a relative risk aversion of 2 and a total response cost of 25% relative to the wealth of the country.

FIGURE 12. Scenario A vs B: Welfare gain from AI product

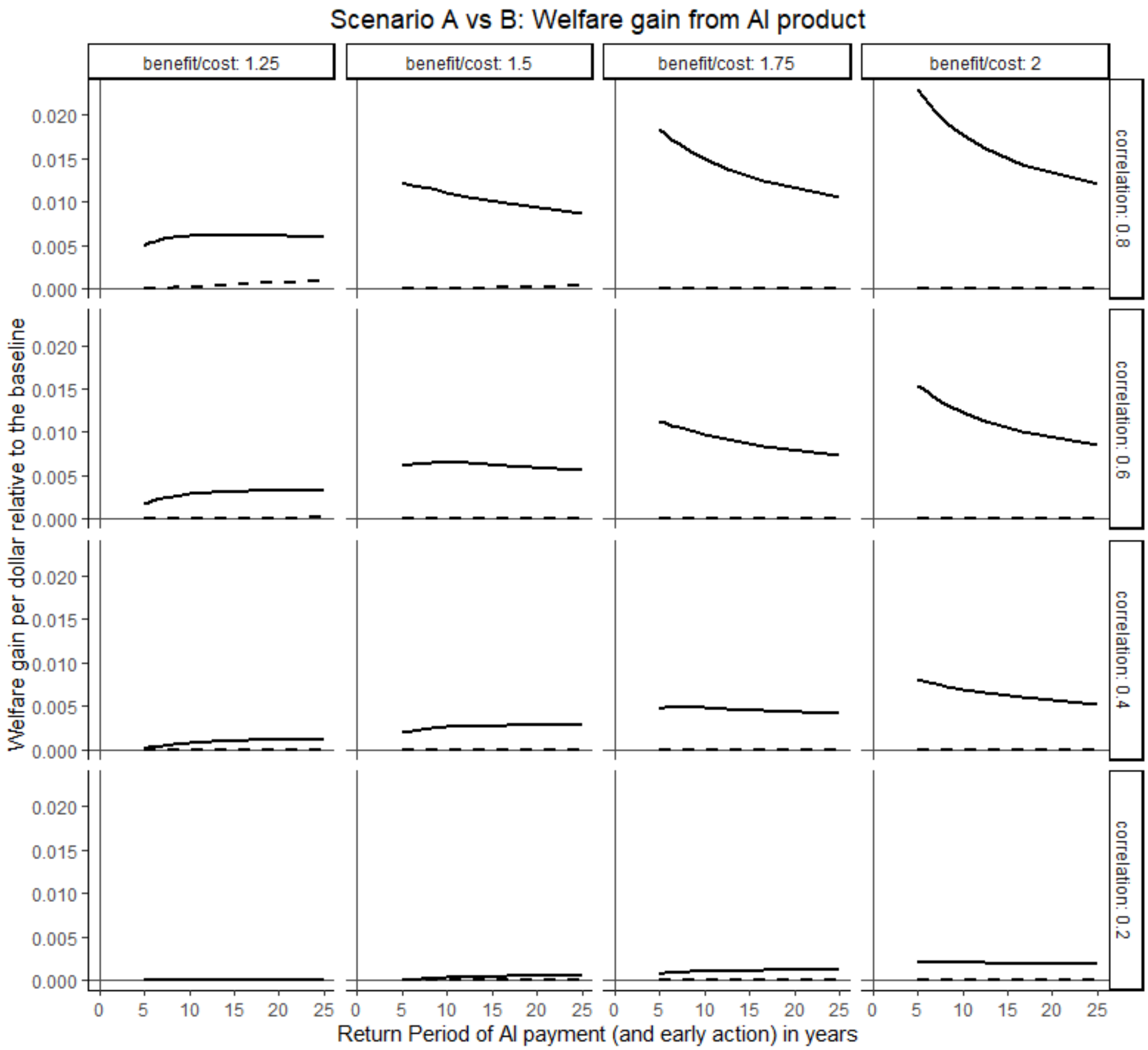

Figure 12. The figure plots the welfare gains (as a fraction of the baseline welfare) from AI product under the two counterfactuals, for different values of basis risk, return period, premium loading, and benefit-to-cost ratio of early actions. The solid line in the graph corresponds to counterfactual 1 that assumes a baseline scenario where the country does not self-finance the forecast-based early actions. The dashed line in the graph corresponds to counterfactual 2 that assumes a baseline scenario where the country self-finances the forecast-based early actions. The x-axis on each graph is the return period of the loss event covered. The y-axis on each graph is the welfare gain as a fraction of the baseline welfare. There are 16 panels based on different values of basis risk (i.e., correlation between the occurrence of drought and the triggering of the AI product payment) along the rows and benefit-to-cost ratio of early actions along the columns. We assume the premium loadings of 35% for AI product. The analysis assumes a relative risk aversion of 2 and a total response cost of 25% relative to the wealth of the country.

FIGURE 13. Scenario A vsC: Welfare gain from AI vs FbF Capacity: No self-funding for early action

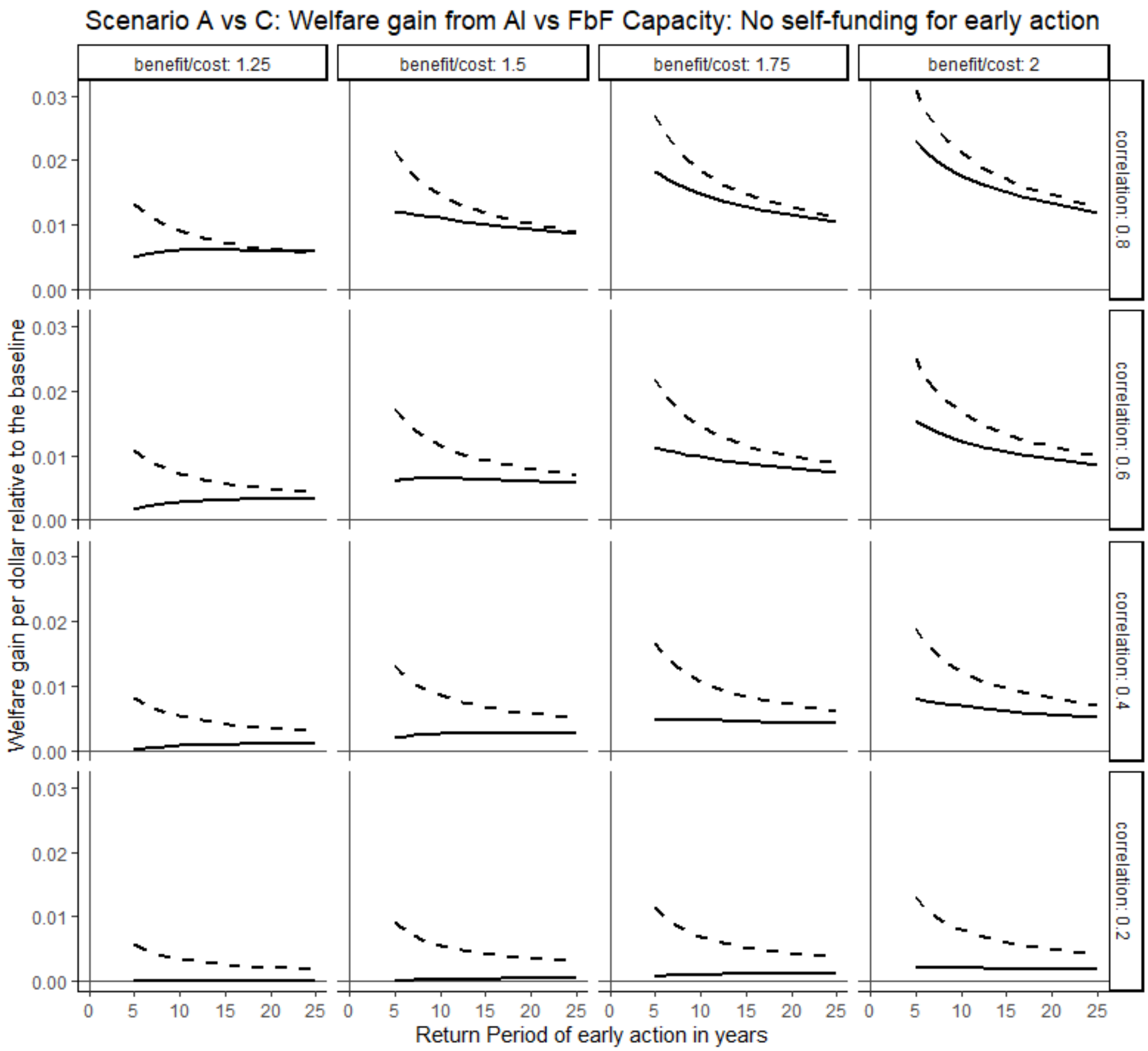

Figure 13. The figure plots the welfare gain from the AI product (solid line) relative to the FbF building support (dashed line), as a fraction of the baseline welfare, for different values of basis risk, return period, premium loading, and benefit-to-cost ratio of early actions. The analysis assumes a baseline scenario where the country does not self-finance forecast-based early actions in the absence of the AI product or the FbF capacity-building support. The x-axis on each graph is the return period of the AI product payment or the early actions financing. The y-axis on each graph is the welfare gain as a fraction of the baseline welfare. There are 16 panels based on different values of basis risk (i.e., correlation between the occurrence of drought and the triggering of the AI product payments) along the rows and benefit-to-cost ratio of early actions along the columns. We assume the premium loadings of 35% for the AI product. The analysis assumes a relative risk aversion of 2 and a total response cost of 25% relative to the wealth of the country.

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