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MITIGATING THE ADVERSE EFFECTS OF CLIMATE CHANGE IN DEVELOPING COUNTRIES: THREE ESSAYS

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Résumé

Cette thèse s'appuie sur trois essais empiriques intégrant des questions environnementales et agricoles à l'économie du développement et documentant la résilience des ménages au changement climatique en Afrique sub-Saharienne.

Le Chapitre 1 s'interroge sur les effets potentiellement adverses de la caution solidaire sur les investissements agricoles dans l'adaptation au changement climatique, du fait des désincitations à l'effort et du phénomène de passager clandestin qu'elle peut impliquer. J'étudie le cas particulier du Burkina Faso où la caution solidaire régit l'organisation des coopératives de coton et conditionne l'emprunt des intrants. En s'appuyant sur une enquête de 668 producteurs de coton, les résultats suggèrent que plus la coopérative est grande, plus ses membres se détournent des stratégies individuelles de lutte contre le changement climatique.

Le chapitre 2 évalue l'impact moyen et la validité externe des assurances indicielles sur les décisions de production agricole. En rassemblant les données de six essais randomisés contrôlés dans un modèle Bayésien hiérarchique, nous montrons que les programmes d'assurance indicielle ont le potentiel de favoriser les investissements productifs des agriculteurs, mais que cet effet est beaucoup plus incertain que lorsqu'il est estimé par une méthode de méta-analyse classique. L'importante hétérogénéité des effets de traitement détectée entre les études génère une incertitude non négligeable autour de l'effet de l'assurance indicielle dans un nouveau contexte. L'analyse des covariables suggère que les ménages les plus pauvres et moins destinés à des performances agricoles bénéficient davantage de l'assurance indicielle.

Le chapitre 3 s'appuie sur le cas de la Grande Muraille Verte (GMV) au Nigéria pour quantifier les retombées d'un programme de restauration environnementale sur la santé des enfants. En exploitant l'hétérogénéité géographique et temporelle de l'exposition des enfants aux activités de la GMV, nous estimons les différences d'évolution sanitaire entre les groupes de contrôle et de traitement par la méthode des doubles-différences. Nous montrons qu'une amélioration substantielle et significative de la santé, mesurée par l'écart type de la taille pour l'âge, s'opère chez les enfants vivant à proximité des vergers communautaires. L'étude des mécanismes explicatifs suggère que les enfants proches des vergers accèdent à des régimes alimentaires plus diversifiés, bénéficiant ainsi d'une meilleure sécurité alimentaire.

Summary

This dissertation provides three empirical essays related to environmental and agricultural issues in development economics, documenting households' resilience to climate change in Sub-Saharan Africa.

Chapter 1 investigates whether joint liability in agricultural cooperatives negatively affects investments in climate change adaptation strategy through disincentives for increasing effort levels and free-riding behavior among group members. I explore the case of Burkina Faso where cotton farmers are organized under the joint liability system. Using a unique survey of 668 cotton producers, I proxy peer pressure by the size of the network and find it to be associated with reduced investment in self-protection against weather shocks.

Chapter 2 studies the impacts and external validity of index insurance programs on agricultural decisions. Using data from six randomized controlled trials and a Bayesian framework, we show that index insurance has the potential to foster the productive investments of farmers but that these effects are much more uncertain than suggested by the pooling model. The substantial heterogeneity detected in the by-study treatment effects generates high uncertainty for the predicted effect of the programs in a new context. We also find some evidence that treatment effects are higher for households with low level of predicted outcomes and lower wealth index.

Chapter 3 uses the implementation of the Great Green Wall (GGW) project in Nigeria to document the local impact of environmental restoration activities on children's health. We exploit geographical heterogeneity of children in exposure to GGW projects and conduct a difference-in-difference analysis. We find a significant health improvement for children living next to community-based orchards whereas proximity to shelterbelts generates mixed impacts. Further results confirm that the observed increase in height-to-age occurs through better food security, in particular with higher dietary diversity score for children living near orchards.

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Introduction

Sur les côtes du Sénégal, l'érosion des sols et la montée des eaux rongent les dunes de sable qui protègent les maraîchers de la puissance marine. Dans les terres arides du Burkina-Faso, les plus vieux baobabs promis à une existence centenaire plient sous le poids de la chaleur et meurent par milliers. Au croisement du Tchad, de la Libye, du Niger et du Nigeria, l'incontournable lac Tchad a perdu 90% de son volume en eau sur les soixante dernières années. Les frontières se traversent sans que l'histoire ne s'interrompe, désignant un ennemi commun : le changement climatique. Cette thèse raconte l'histoire d'un continent qui se réchauffe inexorablement et enterre ses écosystèmes un à un, et qui pourtant, ne cesse d'innover pour se tenir debout et vivre.

Avec un niveau de fiabilité scientifique rarement égalé, le sixième rapport du Groupe d'experts Intergouvernemental sur l'Evolution du Climat (GIEC) dresse un constat vertigineux sur l'avancement du réchauffement climatique (Masson-Delmotte et al., 2021). Le futur esquissé par les différents scénarios d'évolution du climat n'est guère plus réjouissant. Dans tous les cas de figure considérés par le GIEC, la température va continuer d'augmenter dans les vingt prochaines années en Afrique. Des vagues de chaleur extrême, d'intensité toujours plus accrue, déferleront plus souvent sur le continent. Les saisons des pluies, toujours plus tardives, pourraient se caractériser par une hausse des épisodes de fortes et soudaines précipitations, propices aux inondations. Dans un contexte où les moyens de subsistance dépendent majoritairement de l'agriculture pluviale, ces changements vont exercer une pression supplémentaire sur les revenus agricoles et la vulnérabilité des ménages ruraux d'Afrique Sub-Saharienne (Rockström and Falkenmark, 2015). Le réchauffement climatique fait ainsi peser une menace croissante sur le bien-être d'une population qui n'est pourtant qu'à l'origine de 2% des émissions mondiales de dioxyde de carbone.[1]

De tout temps, les agriculteurs de la région ont rivalisé d'ingéniosité pour se protéger des effets adverses du changement climatique en adoptant des stratégies de gestion du risque telles que la diversification des sources de revenus (Barrett et al., 2001; De Janvry and Sadoulet, 2001) ou le recours à des mécanismes de mutualisa-

[1] Calcul de l'auteur à partir des données d'émissions de CO2 au niveau mondial et au niveau de l'Afrique sub-Saharienne disponibles pour l'année 2018 sur le site de la Banque Mondiale.

tion du risque entre personnes d'une même communauté (Udry, 1994; Dercon et al., 2006). La liquidation des actifs du ménage en cas de choc (Fafchamps et al., 1998; Kazianga and Udry, 2006), en particulier le bétail, et l'emploi de techniques de production à bas-risque/bas-rendement (Rosenzweig and Binswanger, 1993; Morduch, 1995; Dercon and Christiaensen, 2011) constituent également des leviers d'action importants dans l'atténuation du risque climatique. Malgré l'éventail des stratégies d'adaptation mises en œuvre par les agriculteurs de la région, leur vulnérabilité économique reste importante, et ce pour deux raisons. D'une part, le caractère covariant du risque climatique, c'est-à-dire sa distribution homogène au sein d'une même communauté, met à mal certaines stratégies de mutualisation du risque puisque les habitants d'un même village ou d'un même réseau se retrouvent tous négativement impactés par le même choc (Kazianga and Udry, 2006). D'autre part, ces stratégies d'adaptation conduisent souvent les ménages à repousser des investissements potentiellement bénéfiques afin d'échapper au principe de solidarité inhérent au fonctionnement de leur société (Baland et al., 2011; Jakiela and Ozier, 2016; Boltz et al., 2019). La redistribution des gains économiques imposée par certains mécanismes de mutualisation des risques peut en effet conduire des agriculteurs à limiter leur performance potentielle. Le chapitre 1 de cette thèse s'inscrit dans cette littérature en démontrant que la caution solidaire imposée aux coopératives de coton du Burkina-Faso ralentit les investissements dans les techniques agricoles visant à protéger les cultures de l'aléa climatique. En relâchant les contraintes pesant sur les agriculteurs productifs, des outils de gestions du risque plus formels et institutionnalisés, tels que le crédit ou l'assurance, peuvent encourager les comportements d'adaptation.

Pour pallier aux limites des mécanismes informels et accompagner les agriculteurs dans leur protection au changement climatique, un nouveau type d'assurance, dit « indiciel », se développe depuis quelques années (Alderman and Haque, 2007; Mahul and Stutley, 2010). Contrairement à l'assurance agricole traditionnelle qui indemnise l'exploitant sur la base de perte ou dommages des récoltes mesurables, les indemnisations de l'assurance indicielle s'établissent en référence à un indicateur indirect censé être un « proxy » des dommages. Les assurances météo-indicielles, par exemple, fournissent des versements en fonction de l'évolution d'un indice basé sur des variables météorologiques telles que la pluviométrie ou la température. Le versement des indemnisations se fait alors lorsqu'un seuil considéré comme critique est franchi. Il n'est pas nécessaire d'effectuer de constats sur les parcelles agricoles, ce qui d'une part évite aux compagnies d'assurance les coûts élevés de la vérification des sinistres et les risques d'aléa moral, et d'autre part épargne les agriculteurs de longs délais de vérification et d'indemnisation des sinistres. Un nombre croissant d'évaluations d'impact suggère que l'assurance indicielle aide les agriculteurs dans leur combat contre le risque climatique et les encourage à adopter des techniques agricoles plus productives (Karlan et al., 2014; Carter et al., 2018; Janzen and Carter, 2018; Hill et al., 2019). En rassemblant les données de plusieurs essais contrôlés randomisés, le chapitre 2 de cette thèse agrège la connaissance scientifique sur l'assurance indicielle et quantifie l'effet moyen de ces programmes sur les décisions de production des agriculteurs dans les pays en voie de développement. Cette méta-analyse suggère ainsi que l'impact de l'assurance indicielle sur les décisions de production est incertain et hétérogène et défie l'idée que ces produits assurantiels encourageraient les agriculteurs à investir dans des techniques ou intrants agricoles plus productifs.

Les systèmes de gestion du risque formels comme informels se révélant parfois défaillants, les décideurs politiques se sont plus récemment intéressés à des programmes de protection visant à soutenir des moyens de subsistance plus durables. Les filets sociaux de sécurité ont graduellement émergé comme l'une des politiques publiques les plus populaires pour réduire la pauvreté et la vulnérabilité des ménages dans les pays en développement (Grosh et al., 2008). Parmi ces programmes, certains, souvent décrits comme des filets de sécurité environnementale, s'attèlent à faire de la nature et des écosystèmes une source d'amélioration des conditions de vie locale (Fisher et al., 2010; Pritchard et al., 2020). Cette alternative part du principe que la résilience des ménages est directement déterminée par la qualité des écosystèmes dont ils dépendent largement pour vivre. Ces solutions, basées sur la nature, couvrent un large éventail d'activités accompagnant la conservation, la gestion durable, et la restauration des écosystèmes. Ces interventions sont d'autant plus urgentes que l'Afrique sub-Saharienne subit une dégradation sans précédent de la qualité de ses terres arables à la suite du réchauffement climatique (Sivakumar, 2007). Le processus de désertification à l'œuvre dans cette région menace la productivité agricole, la sécurité alimentaire et plus généralement le bien-être de millions d'individus établis sur ces terres brûlées (Couttenier and Soubeyran, 2014; Olagunju, 2015). Pour freiner et prévenir la stérilité des sols, onze Etats de la bande sahélo-saharienne se sont accordés en 2007 sur un projet ambitieux de reforestation de 7000 km, courant de Dakar à Djibouti. Son envergure spatiale, le nombre de villages impliqués dans les activités de restauration, et le montant des fonds alloués à sa mise en œuvre font de la Grande Muraille Verte le filet de protection environnementale actuel le plus ambitieux du territoire africain. Le chapitre 3 de cette thèse confronte ces ambitions à la réalité en évaluant l'impact des projets Nigérians sur la santé des enfants.

En s'inspirant de la tendance actuelle des thèses en économie, ce manuscrit compile trois essais qui contribuent à la littérature récente sur les questions environnementales dans les pays en voie de développement (Greenstone and Jack, 2015). Indépendants les uns des autres, les chapitres possèdent leur propre introduction, méthodologie, base de données et résultats. Le choix des pays d'étude (le Burkina-Faso et le Nigéria) découle naturellement de la disponibilité des données et de leur pertinence dans l'illustration de la question de recherche. La diversité des terrains d'étude et des méthodologies mobilisées ne doit cependant pas faire oublier que ces travaux sont le fruit d'une réflexion globale sur la résilience des ménages installés dans des zones durement frappées par le changement climatique. En particulier, ces chapitres prêtent attention à certains aspects de la résilience encore négligés dans la littérature économique et espèrent apporter des outils d'aide à la conception de politiques publiques plus efficaces. La suite de cette introduction propose un résumé de chacun des chapitres. Enfin, les implications des résultats suggérés par cette thèse, ainsi que les recommandations de politiques économiques associées, sont détaillées en conclusion.

Chapitre 1 "Forced solidarity and adaptation to climate change: evidence from Burkina cooperatives".

Au Burkina-Faso, un système de mutualisation du risque est imposé à tous les producteurs de coton appartenant à une coopérative. Les compagnies cotonnières du pays approvisionnent en intrants les coopératives qui sont ensuite chargées de les redistribuer à leurs membres au début de la saison agricole. A la fin de la saison, les agriculteurs ont l'obligation de rembourser sous forme de coton la part d'intrants qui leur a été allouée. Si l'un des agriculteurs échoue à rembourser sa part de l'emprunt, les autres membres de sa coopérative doivent prendre en charge son dû en cédant davantage de leur récolte. Ce principe, plus connu sous le nom de « caution solidaire », permet aux agriculteurs d'atténuer la variabilité de leur revenu. Cependant, la caution solidaire peut également générer des effets inattendus et contre-productifs en termes d'adaptation au changement climatique. En effet, l'assurance d'être soutenu financièrement par ses pairs peut générer un comportement de passager clandestin de la part de l'agriculteur qui, se sachant protégé, ne produit plus autant d'effort pour s'adapter au changement climatique. Le devoir de partage peut également démotiver certains agriculteurs à investir dans des stratégies d'adaptation, dès lors qu'ils se verront potentiellement forcés de partager le fruit de leur investissement avec leurs collègues.

L'organisation des coopératives de coton au Burkina Faso offre donc un cadre intéressant pour étudier les interactions entre les stratégies collectives et individuelles de gestion du risque. Une des originalités de ce papier est d'explorer l'impact de la pression à la redistribution sur la gestion du risque dans le milieu professionnel. Jusqu'à présent, la littérature académique portait davantage son attention sur la pression à la redistribution dans la sphère familiale. Mettre en avant les effets potentiellement pervers de l'obligation de redistribuer ses ressources permet de mieux éclairer les débats sur l'organisation de la filière cotonnière très présente dans toute l'Afrique sub-Saharienne.

Ce travail de recherche repose sur une enquête menée auprès de 668 producteurs de coton durant la saison agricole 2015/2016. Un modèle à variable dépendante binaire est utilisé pour évaluer l'impact de la pression à la redistribution, mesurée par la taille de la coopérative, sur les décisions d'adaptation. Les résultats, robustes et significatifs, montrent que le mécanisme de gestion du risque collectif s'effectue aux dépens des stratégies individuelles de gestion du risque. En particulier, les producteurs de coton opérant sous la tutelle de plus grandes coopératives ont une probabilité plus élevée de ne pas mettre en œuvre de mécanismes d'adaptation au changement climatique. Cette décroissance de l'effort de résilience s'explique en partie par l'existence de la caution solidaire qui décourage l'investissement dans des stratégies d'adaptation.

Chapitre 2 "Index Insurance and Agricultural Decisions: Assessing the External Validity of Multiple Randomized Controlled Trials" co-écrit avec Jules Gazeaud.

En 2019, le prix Nobel en Economie récompense les travaux consistant à adopter la méthode des essais cliniques aux interventions en matière de développement. Cette attribution est le point d'orgue d'une décennie marquée par l'explosion du recours aux essais randomisés contrôlés pour répondre au défi de l'identification causale. La littérature sur les assurances indicielles n'y fait pas exception. Nombre d'études expérimentales se sont ainsi déroulées et empiriquement démontré que les produits d'assurance indicielle encouragent la prise de risque des agriculteurs dans les pays en développement. Cependant, ces études pâtissent d'une faible validité externe, c'est-à-dire qu'elles sont très localisées et spécifiques à des régions, des climats, ou des coutumes, entre autres caractéristiques. Leurs résultats sont donc difficilement généralisables et compliquent la capacité des décideurs politiques à s'en inspirer pour mettre en oeuvre des programmes similaires dans leur pays.

Cette analyse entend combler le manque de preuve de la validité externe des assurances indicielles en fournissant une évaluation empirique de (i) l'effet moyen des programmes sur les décisions de production agricole, (ii) le degré d'hétérogénéité de l'effet de traitement entre les études, et (iii) les sources potentielles de l'hétérogénéité. Pour atteindre ces objectifs, nous mobilisons le modèle hiérarchique Bayésien dans lequel nous rassemblons les données de six essais contrôlés randomisés. La sélection des papiers retenus pour cette méta-analyse est déterminée par des critères d'inclusion définis au préalable et par la mise à disposition des données par les auteurs respectifs. Les décisions de production agricole, sur lesquelles nous concentrons notre analyse, s'illustrent au travers de cinq variables : la surface de terres cultivées, les dépenses en pesticides, en semences, en engrais, et un indice de risque du portefeuille des cultures. Afin de mieux appréhender les origines de l'hétérogénéité de l'effet de traitement entre les études, les covariables de la taille du ménage, de l'âge et du niveau d'alphabétisation du chef de ménage, l'indice de richesse, et les variables dépendantes prédites sont distinctivement étudiés.

Les résultats de cette étude suggèrent que les programmes d'assurance indicielle ont le potentiel de favoriser les investissements productifs des agriculteurs, mais que cet effet est beaucoup plus incertain que lorsqu'il est estimé par les méthodes de méta-analyse classiques. L'effet de l'assurance indicielle sur les décisions de production est également très hétérogène d'une étude à l'autre, ce qui affaiblit la validité externe des résultats. Autrement dit, si les décideurs politiques devaient mettre un programme similaire sur un nouveau terrain, la possibilité d'obtenir des effets négatifs ou nuls de l'assurance indicielle ne serait pas négligeable. Par exemple, l'effet de traitement prédit sur la surface des aires cultivées a 25% de chances d'être négatif dans une nouvelle étude. L'analyse des covariables individuels n'explique que partiellement l'hétérogénéité de l'effet de traitement. Nous trouvons ainsi que les ménages les plus pauvres et les moins promis à des performances agricoles bénéficient davantage de l'assurance indicielle. Ce résultat met en lumière la relative capacité des programmes d'assurance indicielle à accompagner les ménages les plus vulnérables dans leurs investissements productifs.

Chapitre 3 "The Great Green Wall, a bulwark against children's food insecurity? Evidence from Nigeria" co-écrit avec Antoine Leblois.

En s'appuyant sur le cas précis de la Grande Muraille Verte au Nigéria, ce chapitre se donne pour objectif de quantifier les retombées d'un programme de restauration environnementale sur la santé des enfants. Cet article est notamment le premier à mobiliser les outils de l'analyse d'impact pour établir un lien causal entre la Grande Muraille Verte et des indicateurs de bien-être. L'analyse arrive dans une période où plusieurs voix institutionnelles et journalistiques se sont élevées pour réclamer aux scientifiques des preuves empiriques sur la capacité du programme à tenir ses objectifs de développement.

Pour ce faire, nous mobilisons les données issues des Demographic Health Survey (DHS) disponibles pour le Nigéria et couvrant la période de mise en oeuvre du programme (2013-2018). Ces dernières incluent des variables anthropométriques reconnues comme étant de fiables indicateurs du niveau de santé des enfants, notamment la taille-pour-l'âge qui constitue notre variable dépendante de référence. Des échanges avec les membres de l'Agence Nationale de la Grande Muraille Verte au Nigeria nous ont également permis de cartographier les différentes activités rattachées au programme sur le territoire national. Dans la spécification principale, l'enfant est considéré comme étant exposé au programme s'il vit à moins de 15 kilomètres d'un projet de la GMV. En exploitant l'hétérogénéité géographique et temporelle de l'exposition des enfants aux activités de la GMV, nous estimons les différences d'évolution sanitaire entre les groupes de contrôle et de traitement par la méthode des doubles-différences. En mobilisant également les DHS disponibles pour 2003, nous nous assurons que les dynamiques pré-programme sont similaires entres les deux groupes, validant l'hypothèse de tendances parallèles. Les conditions sanitaires étant largement déterminées par le niveau de sécurité alimentaire, nous répliquons notre analyse sur l'indice de diversité alimentaire des enfants afin de mieux appréhender les canaux à l'oeuvre.

Deux résultats notables se dégagent de cette étude. Premièrement, une amélioration substantielle et significative de la santé, mesurée par l'écart type de la taille pour l'âge, est à l'oeuvre chez les enfants vivant à proximité des activités de la GMV. Lorsque l'activité en question est un verger communautaire, cette observation se maintient à travers toutes les spécifications. L'analyse empirique apporte des résultats plus mitigés sur le bénéfice des brise-vents, l'autre catégorie de projet impliquée dans le programme. Deuxièmement, l'indice de diversité alimentaire des enfants vivant aux alentours de vergers connaît une hausse également significative, démontrant par-là que la meilleure santé des enfants locaux est notamment permise par un meilleur accès aux denrées alimentaires.

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Chapter 1

Forced solidarity and adaptation to climate change: evidence from Burkina cooperatives

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1.1 Introduction

A wide variety of risks, including climate-related risks, threatens the African agricultural sector. In Africa, agriculture is mostly rain-fed and depends heavily on precipitation, which varies intra-annually, inter-annually, and spatially (Sivakumar, 1988; Sultan et al., 2005). Observations of past data in Sub-Saharan Africa have shown an increasing variability of climatic variables in recent decades, and this trend is expected to continue during the 21st century (Cook and Vizy, 2006; Kotir, 2011; Field et al., 2014). There are large regions of Sub-Saharan Africa where climate change will affect agricultural production and make farmers reconsider their management systems in favour of more resilient strategies. Burkina Faso, where cotton production is at the core of many households' livelihoods, is one of them. The cotton yields in West Africa have been shown to be very sensitive to 3 main climatic features: rainfall, humidity and temperature, and solar radiation (Blanc et al., 2008).

Climate variability will continue to affect cotton yields in Burkina Faso and reinforce the need for adaptation. Geographic and socio-economic environments shape a household's choice of adaptation strategies, by fostering, or constraining, its ability to adapt. The socio-economic characteristics of the household, market conditions, biophysical aspects, characteristics of adaptation practices, and other local features are key determinants for the implementation of climate risk mitigating strategies (Hassan and Nhemachena, 2008; Bezabih and Sarr, 2012; Bryan et al., 2013; Angelsen et al., 2014; Antwi-Agyei et al., 2018). This paper investigates an additional factor associated with adaptation to climate change which has been rarely, considered in the economics literature: mutual assistance between farmers. Specifically, the purpose of this paper is to understand whether mutual assistance inside cooperatives correlates with a willingness to self-protect against climate change.

To reduce the risks of agricultural activities, risk-pooling via both formal and informal structures is a normal approach. In Burkina Faso, a compulsory risk-pooling mechanism has been implemented in the cotton sector to protect farmers from negative shocks. Cotton farmers are gathered into formal groups to get access to inputs from cotton companies. At the end of the agricultural season, producers must pay back their own part of the loan to the company through harvested crops. The joint liability system is one of the key components of risk-pooling in this organization.[1] This system implies that the crop failure of one farmer must be compensated by other farmer members of the group. Sharing obligations within their professional network allow farmers to mitigate harmful impacts from shocks. However, this sharing may come at a cost, because of potential negative incentive effects. Compulsory sharing generates free-riding behaviour by reducing the incentives for self-protection as farmers can fall back on other members. Sharing obligations may dissuade farmers from working hard, or investing in infrastructure, because the more successful farmers are likely to be forced to assist other members of the network.

The cotton sector in Burkina Faso provides a clear example to better understand the interplay between risk-pooling strategies and individual farmer's management decisions against the threat of climate change. This paper aims to make two main contributions. First, it explores the behavioural impacts of redistributive pressure in the farmers' professional network. A professional network has rarely been considered as a source of pressure in academic studies, especially when compared to kinship ties. Yet cooperatives are professional environments where the joint liability condition puts pressure on farmers. This paper provides information for policy makers and cotton companies about the effects of sharing obligations by conducting a study in Burkina Faso where the economic implications of cooperatives have not yet been analysed. Pointing out the adverse effects of purchasing in a joint liability mechanism in agricultural activities is important, because this form of organization is legally enforced in the whole of Burkina Faso, and acts as a role model for neigh-

[1] In this case joint liability denotes the obligation of two or more partners to share responsibility for making a payment.

bouring states involved in cotton growing, such as Mali and Cameroon.

The second original feature of this paper is to identify two types of adaptation strategy and analyse how each of them is correlated with group lending. Over the years, farmers have undertaken important strategies and practices to adapt to climate-related risks and reduce their vulnerability (Thomas et al., 2007; Bezabih and Sarr, 2012; Bryan et al., 2013; Elum et al., 2017). The Intergovernmental Panel on Climate Change (IPCC) suggests a categorization for these strategies: "incremental" or "transformational" (Field et al., 2014). Incremental adaptations involve efforts to make existing locations, livelihoods, and systems more resilient to climate change. For cotton production in Burkina Faso, incremental adaptations by farmers might consist of improving soil and water conservation techniques, both crucial to an optimal crop growth.[2] However, undertaking exclusively incremental adaptations may lead to a maladapted response in the long term, because the risk of rainfall variability is expected to increase and threaten rain-fed agricultural production. Some authors argue that instead of trying to preserve existing practices, adaptation strategies in developing countries need to become more transformational (Kates et al., 2012; Castells-Quintana et al., 2018). By transformational, they mean adaptation strategies which aim to reduce vulnerability to climate change through geographical and sectoral mobility of poor people.

To guide the empirical analysis, I use a sample of 668 cotton producers from semi-arid regions of Burkina Faso interviewed during the 2015/2016 agricultural season. I use a probit model, and some extensions as robustness checks (biprobit and ordered probit models), to show that sharing obligations encourages free-riding and reduces the incentives for self-protection against climate change. Instrumental variables are added to the analysis to deal with endogeneity of the network variable. Given that the survey is only conducted for one agricultural season, the different specifications cannot control for potential time invariant characteristics. A causal inference approach would require some additional observations of farmers' perceived pressures that are not available in the questionnaire. This work aims to highlight the correlations between cooperative decisions and individual decisions to adapt to climate change.

The results show that risk-pooling strategies operate at the expense of self-protection techniques to protect against climate change. This distortion effect has an impact on both incremental and transformational strategies, hampering the adoption of risk-mitigating strategies beyond the case of cotton management. This result is stronger when farmers report that they belong to groups that facilitate both money transfers between members and adaptation to climate change. This supports the hypothesis that the disincentive to adapt partly comes from the joint liability mechanism at the core of the system.

The remainder of this paper is organized as follow: Section 1.2 describes the or-

[2]The common soil and water conservation techniques in Burkina Faso include zai, mulching, diguettes (rock bunds), half-moons, and hedgerows.

ganization of cotton producers in Burkina Faso and relates it to literature and theoretical intuition on sharing obligations. Section 1.3 introduces the research question, the econometric strategy and the data. In section 1.4, the main results along with some robustness checks are discussed. Section 1.5 concludes.

1.2 Context, Literature, and Theoretical Basis

1.2.1 The system of Cotton Producers' Groups

For Burkina Faso, which is a landlocked country, cotton production has been a vital source of export earnings driving economic growth. Over recent decades, Burkina Faso has become the largest cotton producer in West Africa. Being highly dependent on agriculture, Burkina Faso's economy is threatened by shocks that affect crop and livestock agricultural activities, such as weather, pests, and diseases.

The Sudanese and Sudano-Sahelian agro-ecological zones are today the major areas of cotton production. With an average annual rainfall of 600-900 mm, the Sudano-Sahelian zone is classified as a semi-arid region; whereas the Sudanese zone with 900-1100 mm is classified as a sub-humid environment (see Figure 1.1). Farmers are scarce in the Sahelian zone where the arid environment makes growing cotton difficult.

Beginning with the French colonial period and then after independence, the Burkina Faso cotton sector has been mainly owned and managed by French investors and local governments (Schwartz, 1996). After the independence of Burkina Faso, SOFITEX, a state organization, and CFDT, a privately-owned French company were responsible for the cotton sector. Cotton processing and marketing was a system in which SOFITEX provided all the inputs to cotton farmers and were given exclusive rights to purchase the cotton produced by the farmers (Schwartz, 1996). This vertically integrated system reduced the profits of cotton farmers who were left with only a small percentage of the world cotton price.

In 2002, new institutional arrangements reduced the monopsony control of SOFITEX and opened the cotton market to two other companies - Faso Coton and SOCOMA, which operated in different regions of the country. At the same time, the Burkina Faso government partially reduced its ownership to 35% to leave more space for other stakeholders in the leadership of the cotton sector. In this new environment, producers contribute to the negotiation of price levels through a farmers' union called the National Union of Cotton Producers of Burkina Faso (UNPCB). Although some organizational transformation occurred, the cotton sector is still characterized by a high degree of vertical integration. Upstream, the cotton companies act as a monopsony by providing farmers with inputs, credit, and other extension services. Downstream, it operates as a monopoly by purchasing all the cotton harvest from the farmers (Vitale, 2018). Figure 1.1 illustrates the distribution of land between the three cotton companies operating in Burkina Faso.

The 2002 emancipation of cotton farmers in Burkina Faso occurred following a reform in 1996. Before that, farmers were organized under cooperatives through village-scale joint liability schemes called the GV ("Groupements villageois"). With the 1996 reform, the former GVs were replaced by cooperatives called Cotton Producers' Groups (GPC).[3] Under this new arrangement, cotton farmers were supposed to group together by affinity and social preference. These new cotton producers' organizations, controlled by monitoring and joint liability, generated significant improvements both at the farm level (Kaminski and Thomas, 2011; Kaminski, 2014) and on more aggregated agricultural indexes (Kaminski et al., 2011).

Therefore, every Burkina Faso cotton farmer belongs to a GPC. Within the group, farmers are bound by a joint liability to the relevant cotton company. Prior to planting, each farmer informs her GPC about their needs in terms of inputs - mainly seeds and fertilizers. Cotton firms provide the aggregated amount of inputs requested by the GPCs which redistribute them to farmers. At the end of the agricultural season, farmers must pay for their inputs by means of harvested crops, so that they eventually receive the production value reduced by the value of the debt. If one member of the group fails to provide enough crops to meet their liability, other farmers from the same group take over the debts. This organization within the Burkina Faso cotton sector is very close to the concept of group lending programs which provide credit to an individual borrower who is herself a member of a borrowing group. This means that all group members are treated as being in default if any member of the group does not repay their debt.

If a shock affects the income of one of the group members, the sharing rule dictates that other farmers should provide assistance in the form of supplementary harvested crops. I expect these sharing obligations to impact decisions of production of farmers threatened by climate change. Different hypotheses can be formulated about the consequences of such a system on resilience behaviours. The literature on group lending and sharing obligations provides tools to predict how the system enforced in the Burkinabe cotton sector may affect risk-taking behaviours.

1.2.2 Literature on sharing obligations

This paper investigates the potential presence of forced solidarity in agricultural cooperatives. Forced solidarity generally refers to the sharing of obligations that may occur and have negative effects on savings and investments.[4] These sharing obli-

[3] GPC is the acronym of Groupements de Producteurs de Coton, the French and commonly used expression for Cotton Producers' Groups.

[4] In sociology, solidarity relates to strong feelings of social cohesion and togetherness (Durkheim, 1997).

gations come from norms and traditions (within households) or are imposed by a system (such as group lending in cooperatives). The literature on the adverse impact of forced solidarity mostly applies to networks characterized by strong ties, such as kinship. This Burkina Faso case study deviates from this literature, and considers the professional network of cotton farmers as a new framework in which adverse effects of peer pressure may occur. The joint liability mechanism in cooperatives requires farmers to redistribute their harvests towards less productive members, imposing a kind of mutual assistance between them. In addition, the vulnerability of farmers to climate change in these semi-arid regions generally creates some "in-group feelings" in the sense that a common threat boosts social cohesion (Cassar et al., 2011; Voors et al., 2012). Therefore, I believe that a solidarity framework model is suitable for capturing farmers' mutual help in cooperatives, and in-group feelings, in a rural environment where people are frequently exposed to shocks.

Granovetter (1983) makes a distinction between strong ties and weak ties, and considers business networks to be included in the latter. [5] Following Granovetter, the ties binding members from a cooperative can be regarded as weak ties. In his work, he highlights the strength of weak ties in providing new opportunities and shows that the acquaintances outside one's network offer new sources of information about the job market. In the specific context of agriculture in Burkina Faso, the cooperative may represent new opportunities for a farmer to depend on extra income in case of failure of her own harvests, because the inner circle of ties, which are strong ties, might have also been affected by the shock and so may not represent a source of assistance. However, new opportunities brought by weak ties do not translate only into positive economic impacts. For instance, Patacchini and Zenou (2008) show that a higher prevalence of weak ties increases the crime rate in the American economy because delinquents and non-delinquents are in close contact. I now review some adverse effects that could be at stake when weak ties are grouped under joint liability constraints.

Besley and Coate (1995) make the point that group lending may be able to harness social collateral. Under joint liability systems, borrowers may fear the reaction of other group members. If the group is formed with a high degree of social connectedness, this fear may constitute a powerful incentive device, since the costs of upsetting other members in the community may be high. The fear of being socially sanctioned may enhance cooperative members' incentives.

However, the relatively more successful members of social groups would face internal pressures to redistribute their incomes, which would create disincentives to apply effort, take risks, and accumulate capital (Platteau, 2014). The sharing rule compels the more successful members to bear the burden of the less successful in the network. The imperative to redistribute resources may be closer to an informal redistributive tax. Like any tax, this mechanism carries the threat of potential evasive

[5] Weak ties are acquaintances and strong ties are close friends.

response from the most prosperous members (Platteau, 2000; Baland et al., 2011; Squires, 2016). Experimental evidence supports this view, and research has investigated the magnitude of the economic impact of social pressure to share income with kin and neighbours (Beekman et al., 2015; Jakiela and Ozier, 2016; Boltz et al., 2019). For instance, in Tanzania, Di Falco et al. (2018) show that farmers with higher expected harvests discussed seed type with fewer people and obtained fewer actual harvest gains.

From the literature, two ways of managing production or income in response to redistributive pressure from a network can be distinguished. On the one hand, altruism creates an empathy effect and so an incentive to reduce the probability of having to draw on one member's resources. On the other hand, a free-rider effect creates both the temptation to rely on the efforts of other producers, as well as the disincentive to make effort since returns from such investments might be shared with less successful members.

In Burkina Faso, sharing norms are generally strong (Englebert, 1996). Hadness et al. (2013) investigate the productivity level of a small sample of Burkina Faso tailors depending on whether their prospective income was public information in their solidarity network or not. Their results show that compulsory sharing, as well as the expectation of future claims for financial support, significantly hinder entrepreneurial activity. Similarly, Grimm et al. (2017) show that forced redistribution through family and kinship reduces the ability to invest in capital for businesses in Ouagadougou. The empirical evidence based on these two papers finds free-riding behaviours rather than an empathy effect in response to compulsory sharing. Whereas the redistributive pressure from strong ties has been well studied in Burkina Faso, no research has focused on the potential adverse effects which might be driven by the professional network itself. However, feedback from the field has shown evidence of a high prevalence of peer pressure in cotton cooperatives [6]

An under-explored research question is the extent to which this response may lead to to ill-suited economic decisions in the context of climate change. For instance, would individuals reduce their efforts dedicated to their cotton production to avoid resource sharing with their peers? Inversely, would they put additional efforts into production to avoid crop failure and assistance from other members? These questions emphasize the potential impact of a network on incremental adaptation strategies. Intuition first drives me to expect an impact of mutual assistance between farmers on decisions regarding the management of the cotton sector itself, namely incremental adaptations. A further concern occurs regarding transformational adaptations. That said, does the group buying scheme also hamper cotton growers from

[6] A quotation from Paul Gbangou, former cotton producer in Burkina Faso, has been translated into English for the purpose of this paper: "I had to leave the cotton agricultural sector because of GPC. It was exhausting. You work and earn a good harvest, but still suffer at the end because of other farmers who did not work enough." This comes from De Graeve et al. (2017), https://www.bastamag.net/De-la-Francafrique-a-la-corruption-les-dessous-de-la-filiere-coton-au-Burkina.

moving across sectors and space?

1.2.3 Theoretical Basis

In this section, I introduce the theoretical background to look at the impact of peer pressure on the level of effort involved in agricultural production. This is mainly inspired from the work developed by Armendáriz de Aghion (1999) in which she describes the key parameters to take into account in order to optimally design a collective credit agreement with joint liability. Specifically, she studies how the size of the group has an impact on the level of effort involved in production. She shows that a too large group size prevents an optimal arrangement because of the free-riding effect. Armendáriz de Aghion (1999)'s theoretical model is of particular interest to describe how the size of a network may affect the level of productive effort when joint liability is at the core of the system.

In this section, I try to explain the design of farmers' groups in the Burkina Faso cotton sector and deviate from Armendariz de Aghion's model by assuming that the levels of effort and output are common knowledge between members. The aim here is not to solve the equilibrium of the game between actors but rather to understand how an increase in group size will change incentives for effort. Thus, the focus is on the impact of the redistributive pressure, proxied by group size, on productive decisions.

Under the condition that farmers can observe their partners' efforts, they know that there is a desirable Pareto-optimal level of effort which they need to commit to if they want to maximize the joint profit of the group: this is called the cooperative level of effort e^c. If farmers decide to maximize their individual profit level, they play a non-cooperative game with level of efforts e^{nc}. The model first describes the simplest form in which the group includes only 2 farmers, then increases the group size later.

Let us consider that each cotton farmer owns 1 unit of land and asks for 1 unit of input to produce cotton. They either obtain a successful harvest $Y = \overline{Y}$ with probability e or an unsuccessful harvest $Y = \underline{Y}$ with probability $1 - e$. Farmers chose actions, which can be thought of as a level of effort $e \in [0,1]$, for which they incur a strictly convex disutility cost $C(e) = ce^2/2$. Farmers are considered to be risk neutral. Cotton companies and farmers' unions establish the cotton fibre output price (p) and the input prices for farmers (w). At the beginning of the agricultural season, farmers take the prices as given, and make efforts in the production to pay back their debt. At the end of the agricultural season, they are paid p for their output but the input value w is subtracted from their payment. I assume that the farmer can repay her debt only when the output is high enough ($Y = \overline{Y}$), otherwise she defaults and relies on her partners.

In the first case of two symmetric farmers linked by a joint liability agreement, the group defaults when both farmers have poor harvests, as

$$p\overline{Y} - w > 0 > p\underline{Y} - w \tag{1.1}$$

and,

$$p\overline{Y} - w > p(\overline{Y} + \underline{Y}) - 2w > 0 \tag{1.2}$$

Under the joint liability agreement, each farmer's ex-ante expected profit π^i can be written as:

$$\pi^i = e^2[p\overline{Y} - w] + e(1-e)[p\overline{Y} + p\underline{Y} - 2w] - C(e) \tag{1.3}$$

To make it clearer, both cotton producers realize successful harvest $\overline{Y}$ with probability e^2 so that they earn $p\overline{Y} - w$. The probability of 1 farmer defaulting is $e(1-e)$), so that farmer i receives her own surplus from a successful harvest minus the other's deficit, $p\overline{Y} + p\underline{Y} - 2w$.

I next derive the optimal efforts made by farmers when they are jointly liable, to compare it to its counterpart for larger groups, and I derive the optimal efforts for both the cooperative and non-cooperative situations. Within the framework of cooperative efforts, the farmer maximizes the total welfare of the group which ultimately means considering the partner's effort as given and exogenous (noted $\overline{e}$). The optimization of equation (3) offers the optimal non-cooperative effort e^{nc} as the solution of

$$\max_e \pi^i = e\overline{e}[p\overline{Y} - w] + e(1-\overline{e})[p\overline{Y} + p\underline{Y} - 2w] - ce^2/2 \tag{1.4}$$

Using the first order condition and stating $e = \overline{e}$ since a farmer displays symmetric characteristics,

$\overline{e}[p\overline{Y} - w] + (1-\overline{e})[p\overline{Y} + p\underline{Y} - 2w] = ce,$

it is now possible to find e^{nc} so that

$$e^{nc} = \frac{p\overline{Y} + p\underline{Y} - 2w}{p\underline{Y} - w + c} \tag{1.5}$$

The sufficient condition to ensure an interior solution is

$$w - p\underline{Y} < p\underline{Y} - w < c. \tag{1.6}$$

In the case of endogenous effort from other farmers, the optimal cooperative effort is given by

$$\max_e \pi^i = e^2[p\overline{Y} - w] + e(1-e)[p\overline{Y} + p\underline{Y} - 2w] - ce^2/2 \tag{1.7}$$

It implies the following optimal level of cooperative effort

$$e^c = max(\frac{p\overline{Y} + p\underline{Y} - 2w}{2p\underline{Y} - 2w + c}, 0) \tag{1.8}$$

with $e^c < 1$ under (6).

For the given parameters $(p, w, \overline{Y}, \underline{Y}, c)$, $e^c > e^{nc}$ if and only if,

$[p\overline{Y} + p\underline{Y} - 2w][p\underline{Y} - w + c] > [p\overline{Y} + p\underline{Y} - 2w][2(p\underline{Y} - w) + c]$,

which is always true if equation (2) applies.

Extension to larger groups : The theoretical model developed so far has considered the case of only 2 farmers and depicts a situation where effort is assumed to be higher when farmers cooperate. The next question is how efforts would modify if there is a change in the size of the cooperative network? Now, I present the results of the optimal level of effort for n-symmetric farmers.

When turning from a one-to-one situation to a larger group, incentives for efforts are changed in both cooperative and non-cooperative contexts. More farmers in the group means more members to share the deficit of defaulting producers and the probability of more farmers in default. Thus, the size of the group impacts the probability of the distribution of *ex-ante* expected profits.

With n-symmetric risk neutral cotton producers, the cooperative effort resulting from joint-profit maximizing is solved for

$$\max_e \sum_{k=0}^{k=n/2} C_{n-1}^k [e^{n-k}(1-e)^k][p\overline{Y} - w + \frac{-k(w - p\underline{Y})}{n-k}] - C(e) \tag{1.9}$$

Under the cost function specified previously, the first-order condition that determines the optimal effort of a n sized group is

$$\sum_{k=0}^{k=n/2} C_{n-1}^k [p\overline{Y} - w + \frac{-k(w - p\underline{Y})}{n-k}][e^{n-k-1}(1-e)^{k-1}][(n-k)(1-e) - ke] = ce = \Gamma^c(e, n, \Omega) \tag{1.10}$$

where Ω is a vector of parameters $p, \overline{Y}, \underline{Y}$ and w.

If now, the farmers maximize their individual profit and take others' effort as exogenous, the new optimization is :

$$\max_{e} e \sum_{k=0}^{k=n/2} C_{n-1}^{k} [\overline{e}^{n-k-1}(1-\overline{e})^{k}][p\overline{Y} - w - \frac{k(w-p\underline{Y})}{n-k}] - C(e) \tag{1.11}$$

he farmer's problem in the cooperative context leads to the following first order condition

$$\sum_{k=0}^{k=A(n)} C_{n-1}^{k} [p\overline{Y} - w - \frac{k(w-p\underline{Y})}{n-k}] e^{n-k-1}(1-e)^{k} = ce = \Gamma^{nc}(e,n,\Omega) \tag{1.12}$$

The first observation is that $e^{c} > e^{nc}$ as long as $\Gamma^{c}(e,n,\Omega) > \Gamma^{nc}(e,n,\Omega)\ \forall (e,n,\Omega)$. Thanks to previous assumptions made on Ω and the virtue of marginal costs increasing with effort, this finding remains true.

From here, I analyse how the optimal efforts in both cooperative and non-cooperative contexts react to an increase in the size of the group. I simulate Γ^{c} and Γ^{nc} in figures 1.2 and 1.3 to graphically identify the optimal level of effort for different group sizes (n=2, n=6 and n=20) [7].

Figure 1.2 shows that an increase in the size of the professional network generates an ambiguous effect on the optimal level of effort chosen by the farmer. For instance, the optimal cooperative level of effort equals 0.86 when there are only 2 farmers and rises to 0.90 when the group increases to 6 members. However, there seems to be a network size threshold over which farmers belonging to larger groups start to reduce their optimal efforts on agricultural activities ($e*(n=20) < e*(n=6)$). For the non-cooperative framework, the simulated optimal level of effort firstly falls with the increasing size of the network before it rises again. However, optimal efforts in production in Figure 1.3 are always lower than in the case of a 2-player game.

This basic model developed for the specific case of joint liability agreement between cotton producers in Burkina Faso can be encapsulated in the seminal work of Armendáriz de Aghion (1999) which disentangles several effects of the size of the network on borrowers' behaviour. The free-riding effect implies that a larger group size discourages individual monitoring effort whereas other effects counteract it. The figures above illustrate the ambiguous impact of the increase in the size of the network when joint liability agreement is at the core of the system.

In what follows, I liken the variable e to the level of effort to adapt to climate change. I seek to test the prediction that cotton producers' ties affect self-protection

[7] To allow for simulations, I assign values to parameters in the vector Ω while respecting assumptions (1), (2) and (6).

against climate change in Burkina Faso. The econometric analysis helps to solve the directional ambiguity of this impact.

1.3 Data and statistical model

1.3.1 The sample survey

Data for this study come from Pathways to Resilience in Semi-Arid Economies (PRISE), a multi-country research project which has the aim of generating new information about how economic development in semi-arid regions can be made more equitable, and more resilient to climate change.[8] Alongside other case studies, Burkina Faso was considered in analysing the cotton sector in Semi-Arid Lands. To be part of the survey, provinces from Burkina Faso needed to meet several criteria. First, they must have a semi-arid environment to meet the terms of the PRISE project. Second, they must have some cotton farmers.[9] Third, the cotton companies operating in the selected *departements* must be SOFITEX and Faso Coton. [10] The researchers worked closely with these two major cotton companies which both agreed to provide a list of cotton producers in the *departements* of interest.

Following these criteria, three provinces were represented in the survey: Kossi where SOFITEX operates, and Oubritenga and Bam where Faso Coton operates. In the Oubritenga province, households for which the main economic activity consists in farming cotton are located in two *departements*: Nagreongo and Absouya. In total, these two *departements* have 160 farmers. The province of Bam has 475 cotton farmers in 5 *departements* (Kongoussi, Rollo, Tikaré, Sabcé, and Guibaré). Due to the small number of cotton farmers in these semi-arid regions, an exhaustive survey was initially considered there. However, out of the 635 listed farmers in these two provinces, only 524 were present at the time of the survey.

Unlike Bam and Oubritenga, the province of Kossi is a major cotton production zone with approximately 6,033 farmers allocated between 8 *departements*. According to information available from SOFITEX, only Nouna and Doumbala *departements* have a semi-arid environment.[11] Therefore, an additional sample of 144 farmers who grew cotton during the 2015-2016 season was surveyed there. 668 farmers were surveyed in December 2016.

Descriptive statistics for the independent variables are presented in Table 1.1,

[8] This project is led by Overseas Development Institute (ODI).

[9] Although this requirement sounds obvious, some arid or semi-arid agroclimatic zones do not have any cotton producers because of difficult growing conditions for this.

[10] *Departements* in Burkina Faso represent the third administrative division, after Regions and Provinces. They are equivalent to the county level.

[11] SOFITEX uses its own devices to measure rainfall and temperature where its clients are located.

which provides information on several household characteristics - age, literacy, a wealth indicator[12], and agricultural characteristics – the area of land used for cotton production and the labour used per unit of land. For the labour variable, the survey distinguished between male and female employees and between family and paid employees, but I aggregate this information into one labour measure. The labour measure is defined by the total number of workers divided by land units.

The summary table also presents the links of the households to the outside world, including whether the household had access to early warning systems about extreme weather events. Furthermore, it introduces information on the perceived benefits of the GPC system at the individual level. Farmers were asked whether their GPC helps them to adapt to climate change. Later in the questionnaire, they were asked to identify 3 channels through which they take advantage of their GPC. I create a dummy variable equal to 1 if the farmer reports "money transfers between farmers" to be one of the benefits from a group. [13]

Given the dependence on climatic conditions for farming success, I collected monthly rainfall and temperature data using GPS coordinates from the households. Data on rainfall were extracted from CHIRPS database from 1994 to 2016 and allowed computation of cumulative rainfall levels for the agricultural season (from May to October) for each year (Funk et al., 2015). I calculate the ratio of average cumulative rainfall from 2005 to 2016 over average cumulative rainfall from 1994 to 2004. This captures the changes in rainfall during 2005-2016 compared to 1994-2004, and matches the time-scale of the outcome variable. Data on temperature for the period 2005 to 2016 come from MOD11C3 MODIS and were used to establish monthly average temperature for the agricultural season (Wan et al., 2015).

In addition to household questionnaires, investigators obtained the actual number of members in the GPCs during an agricultural season from membership lists provided by the 2 cotton companies. This information was used to check the robustness of our results. Unfortunately, some farmers reported that they belonged to GPCs that are not identified in the list provided by SOFITEX and Faso Coton.

1.3.2 Analytical Framework for the Adaptation Measures

In this section, I introduce the dependent variables. The survey aimed to analyse cotton farmers' adaptation strategies in response to climatic change in Burkina Faso. The questionnaire investigated whether farmers had noticed changes in temperature

[12] The wealth index was constructed following the methodology proposed by the DHS Program, taking into account characteristics such as assets and housing conditions. See https://www.dhsprogram.com/topics/wealth-index/Wealth-Index-Construction.cfm

[13] The questions about help on climate change and channels are independent. A farmer who answers that his/her GPC does not help to adapt to climate change can still choose 3 benefits from their GPC.

and rainfall trends since 2000. 100% of the sample had perceived changes in mean rainfall and 91% in mean temperature, which is consistent with the actual changes in the weather. This observation is in line with Kosmowski et al. (2016) who find that smallholders living in rural dry areas have a higher level of awareness about local changes. The farmers were also asked whether they had responded to these changes by adaptation measures in the last 10 years. I use their answers to distinguish incremental adaptation strategies from transformational adaptation strategies, and analyse the impact of the professional network on both strategies.

The IPCC defines two categories of adaptation strategies in response to climate change (Field et al., 2014). Incremental adaptations are "adaptation actions where the central aim is to maintain the essence and integrity of a system or process at a given scale". These strategies seek to preserve existing locations, livelihoods, and forms of production while making them more resilient. In this context, systems keep their way of functioning with efforts made towards more resilience to climate hazards and to climate change. Alternative definitions of incremental adaptations retain the spirit of the IPCC view. For instance, Fook (2017) describes incremental adaptation as "adjustments made to manage proximate climate risks and impacts while retaining the function and resilience of existing structures and policy objectives".

In contrast, transformational adaptations is an action that "changes the fundamental attributes of a system in response to climate and its effects" (Field et al., 2014). Here, fundamental attributes refer to the function, structure, and identity that characterize a system. By definition, agents carry out transformational adaptations when they seek to reduce vulnerability or exposure to climate change by replacing existing systems with new ones. For example, in the context of this study, transformational actions might be transforming a system based on cotton production to other economic activities. Transformational adaptations, mainly defined as movement of people and activities across sectors and space, describe a long-term process of economic development.

My original hypothesis was that redistributive pressure would have diverse effects on risk-taking whether it relates to cotton production or not. Indeed, although the sharing obligation of the professional network may impact the decisions relative to the cotton sector, it is not clear whether it would also hamper transformational adaptations. Therefore, I follow the above definitions of incremental and transformational adaptations to classify the adaptation actions found in the questionnaire. I create 2 dummy variables, for incremental strategies and transformational strategies, equal to 1 if the farmer reported to have adopted at least one of the strategies referred in Table 1.2. Incremental adaptations focused on improvements in cotton management whereas transformational adaptations focused on alternative livelihood strategies, substitution of crops, or relocation. I exclude adaptation strategies such as change in seeds or fertilizer since those inputs are distributed by cotton companies to the whole cooperative and do not reflect individual choices. Crop rotation is the practice of growing different types of crops and rotating them according to the seasons.

This technique is implemented by the farmer at the plot level and reflects individual choices. I am not aware of any training that would have been offered to the farmers in crop rotation. Since the classification is made arbitrarily according to my own understanding of the 2 concepts, I constrain transformational adaptation to a smaller range of more radical strategies in a robustness check.

1.3.3 Econometric Strategy

The purpose of this paper is to empirically investigate whether a professional network and joint liability reduce the willingness to self-protect in the face of climate change. To estimate how the probability of adopting risk-mitigating strategies is affected by the extent of the professional network, I use the self-reported size of the group and a set of controls. Let A_h^i represent the i-th adaptation strategy (incremental or transformational) for household h. The extent of the network is represented by N_h and associated with the parameter of interest β_1^i. ϵ_h^i is a household specific error terms. X_h and X_h^c are the vectors of household characteristics and climatic variables respectively, with their associated vector of parameters β_2^i and β_3^i.

The empirical is as follows:

$$A_h^i = \beta_0^i + \beta_1^i N_h + \beta_2^i X_h + \beta_3^i X_h^c + \epsilon_h^i \tag{1.13}$$

N_h is the self-reported number of members belonging to the same GPC for household h. Even though the self-reported size of the group may differ from the actual one, it constitutes a good proxy for the scope of the safety network upon which a household feels it relies on for help in times of hardship.

The simplest identification strategy assumes that the size of a farmer"s network is exogenous. This choice is motivated by arguments from the data, the history of GPCs, and some field expertise. First, from field testimonies the farmer is not able to promote competition between cotton companies by choosing, for instance, Sofitex instead of Faso Coton for her cooperative. Figure 1.1 illustrates how the country has divided its territory to let the cotton companies operate geographically as monopoly actors. As well as this monopoly (and monopsony) situation, the cotton companies informally require farmers to work together in a single cooperative per village. The data supports these field testimonies: out of the 32 villages in the sample, 22 (69%) are registered as having only one GPC. Also, new cotton producers are often asked to join already existing cooperatives when they start their business. Cotton companies do not constrain the size of the cooperatives, which leads some of the surveyed groups to have more than a hundred farmers. This pattern shows the limited flexibility farmers can enjoy when it comes to choosing her cooperative, or to creating a new one.

The first econometric specifications for the empirical strategy build on the belief that the main variable of interest is exogenous and is not chosen by the farmer at the time of the survey. However, some theoretical studies highlight pre-existing social networks as a determining factor in group formation. Attanasio et al. (2012) investigate who pools risk with whom when trust is crucial for enforcing risk pooling arrangements. They find that close friends and relatives are more likely to join the same risk pooling group, while non-family non-friend participants join groups less. Therefore professional networks may strongly correlate with networks of kinship, caste, friendship, and geographic proximity (De Weerdt and Dercon, 2006; Fafchamps and Gubert, 2007; Munshi and Rosenzweig, 2009; Mazzocco and Saini, 2012). Because the farmers do not have access to a range of GPC opportunities, it is very likely that most of the cooperatives include members with strong social ties. This is also driven by the fact that the surveyed villages are small. Di Falco and Bulte (2013) find that compulsory sharing within families reduces farmers' incentives to adopt soil and conservation (SWC) techniques. In such a situation, the dependent and independent variables are correlated but the causal effects come from kinship pressure instead of professional pressure.

To improve the chance of capturing the impact of the professional network instead of the kinship network, I add a control. Because there is not enough information from the data to establish potential blood or kinship relationships between farmers, I control for social connectedness by using GPS coordinates to compute the distance between members of the same group.[14] I follow the findings of Fafchamps and Gubert (2007) to control for interpersonal relationships with geographic proximity. The literature often describes geographical proximity as a driver of the monitoring intensity between peers (Armendáriz de Aghion, 1999). Therefore, geographical distance between producers can also be interpreted as an additional measure of social pressure.

The peer effects literature suggests that farmers with similar wealth characteristics are more likely to enter group contracts and share risk (Fafchamp and Lund, 2003; Johnson and Smirnov, 2018). Therefore, characteristics such as land, labour, and other socio-demographic variables, are used as controls to capture individual wealth or endowments. Given the dependence on climatic conditions for farming success, rainfall and temperature information allow the building of an additional specification. Asfaw et al. (2019) show that exposure to climate-related shocks in Sub-Saharan Africa is positively associated with transformational adaptations such as crop or livelihood diversification. In all the specifications, I include a cotton zone fixed effect to control for unobservable heterogeneity for cotton companies (Faso Coton and Sofitex). The last specification controls for *departement* fixed effects. Standard errors are clustered at the village level in the main specifications, but Table A6

[14] The distances are computed through a specific program in Stata using GPS coordinates (geodist). The new variable created captures the mean distance from individual h to all other households belonging to the same GPC.

in the appendix shows alternative clustering.

Although farmers do not enjoy a wide range of opportunities in terms of GPC choice, the reverse causality issue of farmers self-selecting into larger groups cannot be entirely ruled out. It is likely that risk-averse actors would prefer big groups to make sure that they will have assistance from other members in case of harvest failure. That said, the main coefficient could illustrate the fact that risk-averse cotton farmers chose larger groups to broaden their safety network. Therefore, I implement an instrumental probit approach to deal with possible endogeneity of the network variable. The selection of instruments is complex since I need variables that are correlated with the professional network metric but not with the error term of the adaptation models. I provide test statistics to support the idea that instrumentation helps to strengthen the results but neither instrumental variable is perfect.

The first instrument is the total amount of pesticides allocated by cotton companies to farmers for the 2015/2016 agricultural season. The quantity of pesticides distributed to the GPC should be related to the number of members. However, there is no reason to believe that pesticide supply could be correlated with past decisions to adapt to climate change. The pesticide intensiveness on fields is a solution to the risk of crop disease, but not related to weather-related risks. Crop diseases, the cotton bollworm Helicoverpa armigera in particular, represent a major threat for cotton producers in Burkina Faso (Cauquil and Vaissayre, 2000; Banwo and Adamu, 2003).[15] 80 % of the sample reports damage to their cotton production due to crop diseases in the last 10 years. To deal with this common risk, cotton companies provide pesticide to the farmers. This pesticide supply allows the disentanglement of risks induced by climate change from risks induced by pest pressure.

For the next instrument, I make use of the membership history and input data provided by the cotton companies. The second instrument is the lagged actual size of the GPC back to the 2008/2009 agricultural season as recorded by the cotton companies. The size of the GPC in 2008/2009 is likely to explain the self-reported number of members at the time of the survey (2015/2016), because there was no big change in the period. Whether it is correlated to error terms of adaptation measure is more debatable since most of the strategies began to be implemented by farmers after the devastating flood in September 2009. Two of the surveyed provinces, Kossi and Oubritenga, are in the regions which were most affected by this extreme event. The household-level questionnaires show that 78% of the sample suffered from big damage due to the flood.

A further step consists in controlling for heterogeneity between groups of cotton farmers. Including fixed effects at the group level would allow me to tackle unobservable heterogeneity. I use relevant answers from questionnaires to capture het-

[15] cotton bollworm Helicoverpa armigera had high population densities in 1998 leading to massive yield reductions despite increased insecticide use in West Africa. The larvae of the bollworm has the capacity to cause up to 90% yield loss on cotton.

erogeneity between groups of farmers. The survey gives information about the channels through which cotton producers take advantage of their group: GPC may bolster money transfers and/or better management of climate change. Considering the different benefits at the core of different GPCs, different attitudes to risk-mitigation may be triggered. Therefore, I introduce an additional specification with interactive variables to highlight the role of the group organization in the individual decisions to adapt to climate change.

1.4 Results

1.4.1 Main results

The main results are presented in Table 1.3. I focus on the effect of the number of members in the group of cotton producers on both incremental and transformational adaptation strategies. Specification (1) gives the results for the most parsimonious model with household characteristics. Specification (2) controls for weather variables that are most likely to influence adaptation decisions. Specification (3) includes additional fixed effects at the *departements* level. Some robustness checks test for the reliability of the results. Table 1.4 displays the estimates when the endogenous variable is instrumented with one instrument or/and the other.

The first result is that the self-reported size of the network is significantly correlated with a reduced probability to apply incremental adaptation risk-mitigation strategies for cotton growing. This result holds for all specifications, including the instrumental variables model which satisfies the appropriate test statistics. The Wald test shows that the standard probit estimation can be plagued by endogeneity bias (see Wald test statistics at the end of table 1.4). To probe if the instruments are relevant, I run the first-stage regression by regressing the network size variable against the instruments and the other exogenous variables. Both instruments significantly and positively correlate with the network variable.

For incremental adaptations, I estimated the average marginal effect for the network variable, it is -0.002. In other words, one new member joining the GPC reduces the probability of investing in incremental adaptation strategies by 0.2%. If the average group size, which is about 50 farmers, increases by 10%, the individual decision to adapt incremental strategies decreases by 1%. The marginal effects from the instrumental probit regression produces a higher impact, with the same increase in group size leading to a 6.5 % decrease in likelihood to adapt cotton production to climate change. The negative effect of the network size appears to be modest, but should not be underestimated for two reasons. First, field observations prove that one member rarely decides alone to leave one group and join another one. It is more likely that a whole small GPC would ask to merge with another to gain bargaining power against the cotton companies. In this case, the marginal effect on the decision to strengthen cotton production resilience is bigger. Second, existing fieldwork from Burkina Faso suggests that marginal returns on modest investments in water availability may be high in terms of yields (Sanders et al., 1996). Therefore, ignoring adaptation strategies, even though they are not onerous and big, can generate significant losses in yields.

Another interesting variable is the mean distance between one farmer and her GPC partners. When the distance to other cotton farmers increases, the household is significantly less likely to use risk-mitigating strategies for the cotton growing. This result holds only for the first specification. Being another proxy for social pressure, distance captures the similar idea that farmers who belong to an extended network (in space rather than numbers, in this case) have less incentive to consolidate their resilience to climate change. The average marginal effect is approximately -0.005: being even further (about one kilometre) from other members decreases the probability of adopting incremental strategies by 0.5%.

In conclusion, for the incremental adaptation models the results provide significant evidence of negative incentive effects associated with mutual assistance. Under social pressure, farmers behave like free-riders and reduce their willingness to invest in more resilient methods for their cotton production.

Secondly, the estimates for transformational adaptation are qualitatively similar to the ones for incremental adaptation. This result is robust to all specifications for the probit model. However, results for the instrumented specification have not been interpreted since there is no evidence of possible endogeneity in this case (see the Wald test statistics at the end of Table 1.3). Adaptation strategies that could be implemented in parallel to the ones relative to the cotton sector are also negatively impacted by the network of cotton farmers. In addition to hampering risk-mitigating strategies for growing cotton, the structure of the professional network prevents small farmers from diversifying their activities towards other farm and non-farm activities. This means that the professional network impacts risk-mitigation strategies beyond cotton production and constrain farmers from broadening their source of revenues. The average marginal effect is such that one new member in the professional network significantly decreases the likelihood to enforce transformational adaptations by approx. 0.3%. As explained previously, this seemingly modest result can have significant consequences on farmers' livelihoods.

Two interpretations can support this surprising outcome. First, larger networks are more powerful and have more efficient ways to control for potential investment in non-cotton activities. The use of the distributed inputs for alternative crops would be severely reprimanded, for example by exclusion from the GPC, and drive farmers to keep their focus on cotton production. The second explanation is based on the fact that cotton production is the main activity of the surveyed households. Cotton farmers with a larger network have a bigger safety net upon which they can fall back on in bad times. For other crops or activities, a similar risk-protection system does not exist. Therefore, farmers ignore potential alternative sources of income. In small groups however, cotton farmers cannot rely on such an extended network. They generally concentrate on limited issues where they face common risks, such as lack of rainfall, which could cause the whole group to lose their cotton harvest. To plan for this eventuality, farmers in small groups diversify their income sources and enforce transformational strategies to become more resilient to climate change.

Other variables deserve brief investigation to complete the empirical evidence of determinants to adapt in this context. Farmers working on plots where temperature for the last 10 years has been higher on average are significantly more likely to adopt risk-mitigating strategies on their cotton cultivated lands. Moreover, higher levels of rainfall scarcity significantly increase the adoption of transformational strategies. Table 1.3 introduces other interesting determinants of the decision to adapt to climate change that are in line with the previous literature. More educated farmers, who usually benefit from a lower cost of information, have a higher uptake of adaptation strategies. The poorer, small farmers, who have a lower wealth index, are more likely to implement risk-mitigating strategies under the threat of climate change. Since they own less assets, they take more risks to change their farming practices without the fear of losing much in case of failure. In other words, the opportunity cost of changing their daily life in order to adapt to climate change is smaller. Eventually, access to early warning systems significantly drives farmers to adopt transformational strategies by raising awareness of the possible future harmful climatic events.

1.4.2 Channels: the cooperative's features

Additional empirical evidence is crucial to better understand what drives farmers to behave as free-riders when they belong to larger groups. The intuition behind the main results is the following: to mitigate the harmful effects of climate change, smallholder farmers rely on the risk-pooling mechanisms instead of self-protecting. Once they belong to the cooperative, they expect the joint liability system to protect them in case of weather damaging events and the bigger the group, the bigger the probability that they are insured thanks to their peers. I next want to confirm that the risk-pooling system exists in the cooperative and how it affects adaptation decisions according to what extent joint liability is enforced. The aim here is to determine the specific GPC characteristics and conditions under which the results remain true. There are many reasons, other than joint liability pressure, which could drive the correlation between the size of the groups and the decisions to adapt to climate change. The main competitive explanation that might explain a lower likelihood to adopt in larger groups is the slower diffusion of agricultural advice. A larger group could make coordination more difficult, and the transmission of information longer, so that larger groups could tend to adapt later.

To test the assumption that farmers actually consider the cooperative to be a risk-pooling mechanism against climate change, further information is extracted from the data set. Cotton farmers were asked whether the cooperative helps them to adapt to climate change, whether the GPC fosters money transfers between producers, and whether it provides agricultural advice.[16] I run 2 interaction models to separately study the impact of information and the impact of joint liability system according to the size of the group. Also, I run separate regression for *Soil and Water Conservation techniques* (SWC) since the implementation of this incremental strategy may entail an initial cost from which *Rotation of crops* is exempted. I expect the farmers to be more reluctant to adapt to climate change when the adaptation strategies are costly.

Table 1.5 displays the coefficients for the complete interaction term only. I follow advice from Brambor et al. (2006) and did not interpret the coefficients of constitutive terms. However, all the interaction terms are included in the specifications with control variables, and additional results are available in appendices A1 and A2. The results show that when farmers report that they belong to a GPC that both helps to adapt to climate change and facilitates money transfers, the likelihood of implementing SWC techniques is negatively and significantly affected by the size of the group. This result holds also for transformational adaptation strategies. This finding corroborates the intuition that farmers who can financially count on their partners rely on the risk-pooling mechanism to mitigate the harmful impact of climate change instead of implementing new strategies at the individual scale. This holds especially for costly adaptation practices such as investing in alternative SWC techniques.

The main alternative mechanism behind the negative correlation between decisions to adapt to climate change and the size of the cooperative might be assumed to be the diffusion of information and agricultural advice. In larger groups, diffusion of agricultural advice on how to adapt to climate change might be slower and delay the take-up of actions. The results rule out this explanation and show that in larger groups which combine the provision of agricultural advice and some help to fight climate change, farmers are more likely to undertake individual strategies to protect their income.

The interplay between GPC characteristics reveals the settings in which farmers are more likely to adopt free-riding behaviours. The risk-pooling system supplants individual self-protecting strategies to manage climatic risks when cooperatives are proved to enforce joint liability. This free-riding behaviour is strengthened by larger sizes of professional network.

[16] The three questions are distinct from one another.

1.4.3 Robustness Checks

In this section, I check the robustness of estimates by running additional regressions for the most complete probit specification which includes weather variables and fixed effects.

Alternative measures for independent and dependent variables:

Table A3 presents the results for alternative measures of network size. In this model, I test whether the results are robust to the actual size of the network instead of considering the self-reported size of the network. I use information from the two cotton companies who listed the farmers for most of the GPCs and allowed investigators to establish the actual size of groups. Unfortunately, this information was not available for some groups and explains the lower number of observations compared to previous regressions. The results in columns (1) and (2) are qualitatively and quantitatively very close to what was previously found: they show evidence of free-rider behaviour from farmers belonging to larger groups.

I test for a more restrictive interpretation of transformational adaptations to climate change in Table A3, column (3). Transformational adaptations are actions which "change the fundamental attributes of a system in response to climate and its effects". This time, I exclude from the transformational category any strategy that consists in just reorganizing farming activities, and focus on radical actions such as diversification off off-farm activities, total pull out from agriculture, temporal mobility, and migration. Following the new definition, the percentage of farmers who adopted transformational strategies falls from 61% to 29%. Again, incentives to move across space and sector, and to radically change livelihoods, are significantly hindered by larger professional networks.

Extensions to Probit Model:

As a further robustness test, I estimate a bivariate probit model. When we jointly consider the two adaptation strategies, the results are still consistent. The testing procedure on the correlation coefficient of the error terms indicates that the null hypothesis of zero correlation can be rejected, meaning that the two adaptation strategies are often jointly undertaken. Table A4 presents results in line with previous findings.

Finally, I run an ordered probit model to assess how the intensity of adoption is affected by the size of the professional network. For the incremental adaptation, I create a category variable equal to 0 if the farmer did not adopt any strategy - 21% of the sample, equal to 1 if she adopted one strategy – 37%, and equal to 2 if she decided to adopt both SWC techniques and rotation in crops – 42%. Since adaptation strategies defined as transformational are more numerous, I extend the previous categorization to a case where farmers adopt 3 or more transformational actions. The sample has 38% of farmers who did not adopt any transformational strategy, 16%

who adopted 1 strategy, 27% who adopted 2 strategies, and 19% who adopted 3 or more strategies. In sub-Saharan countries, agricultural strategies to adapt to climate change are more effective when they are jointly implemented rather than isolated. For instance, the resilience of farmers who use soil and water conservation techniques increases when these strategies are coupled with change in crops (Di Falco and Veronesi, 2013; Di Falco, 2014). This highlights the importance of not implementing incremental strategies in isolation. The results from Table A5 the size of the cooperative is associated with the highest level of adaptation intensity. Estimated marginal effects for our main variable of interest allow deepening of the understanding: one additional member in the group does not reduce the incentives to adopt at least one adaptation strategy, but decreases the probability of adopting more than one strategy. These results again demonstrate the individual's lax approach to climate change when cooperatives are bigger.

1.5 Conclusion

The anthropological literature pioneered the idea that sharing obligations may lead to negative incentive effects and hold back investment for improving productive activities. Recently, economics researchers have investigated this question but evidence remains incomplete. In this paper, I test this idea by exploring the role of risk-sharing networks on the uptake of weather shock management strategies in Burkina Faso. The results of this empirical analysis indicate that a system based on mutual assistance between farmers may reduce efforts to adopt techniques that mitigate exposure to climate change. This conclusion holds for both incremental and transformational risk-mitigating strategies, showing that the Burkina Faso cotton farm management model has behavioural and economic implications beyond its core sector. This case illustrates that in the farmers' professional network, the principle of forced solidarity (sharing obligations leading to negative economic incentive effects) occurs. This research takes advantage of a range of statistical models which try to establish a significant and robust correlation between the two phenomena. However, these results use exclusively cross-sectional data from one agricultural season, making it complicated to turn the correlations into strong causal inference. Additional data, such as panel data or repeated cross sections, would allow more robust evidence on the role played by mutual assistance in boosting or hampering individual decisions to adapt to climate change.

Analysing how sharing obligations may become a barrier to adoption of new methods is crucial in the Sahelian context. Changing temperature and precipitation levels caused by climate change are expected to threaten rain-fed farming systems, like cotton. It represents an important obstacle for the livelihoods and well-being of farmers in semi-arid lands. They react autonomously to changing environmental conditions by smoothing water availability for their crops or by switching towards activities or to crops less dependent on rainfall levels. However, the existence of compulsory risk management mechanisms may lead farmers to ignore self-protection measures. By requiring producers to join in risk-pooling groups, cotton companies create pressure to redistribute the yields from the more productive farmers to the less successful ones. Therefore, larger groups drive down the incentives to implement autonomous risk-mitigating strategies. However, I do not reject the potential benefits of such a binding joint liability system. For some actors, this form of organization has been proven to be beneficial. On the one hand, the cotton companies which finance the purchases of inputs, can protect themselves from unpaid bills. On the other hand, the cotton farmers may consider these GPC to be a relevant form of safety net when alternative market or institutional mechanisms fail to protect them. However, complementary mechanisms need to be considered to help farmers to reduce their vulnerability to climate change. In the Burkina Faso cotton sector provision of alternative formal risk management mechanisms, such as insurance, is implemented and could be developed to boost decisions to adapt to climate change. By relaxing network pressure on the more productive farmers, group insurance contracts can reduce the likelihood of free-riding on peers to pay for purchases.

Figures and tables

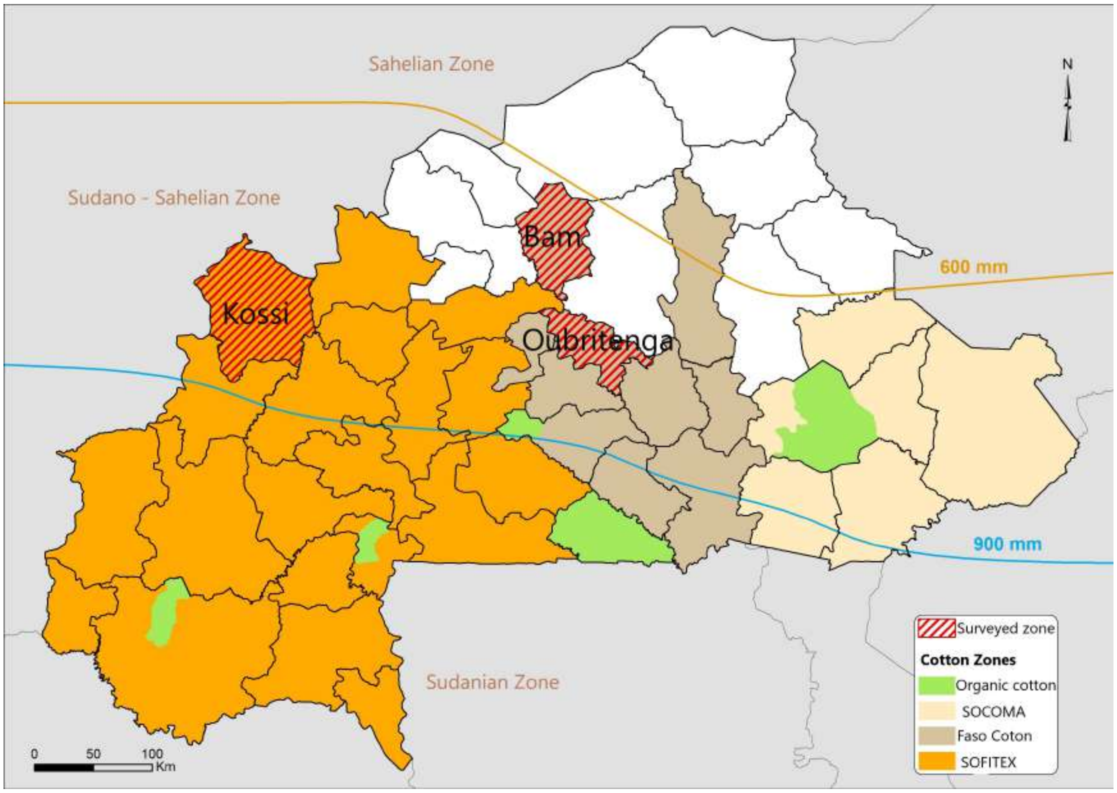

Figure 1.1: Map of Burkina Faso

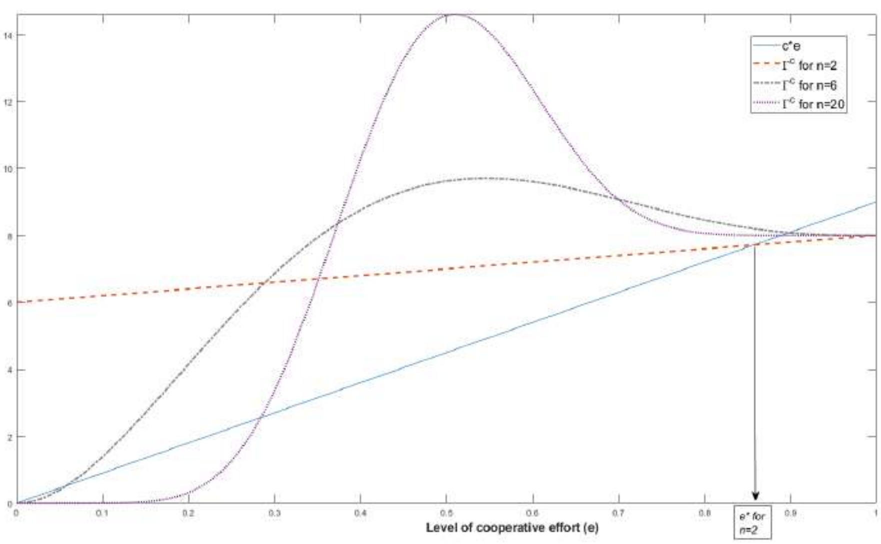

Figure 1.2: Cooperative equilibria of the n-player game.

Table 1.1: Summary statistics for independent variables

Variables [a]	Mean	SD [b]	Min	Max	Obs
Self-reported number of members of the GPC [c]	50.15	39.41	3	136	666
Mean Distance to other farmers in the GPC	2.62	5.58	0	108	665
Age of household head (years) [d]	49.00	12.63	18	88	660
Constructed **Wealth Index**	-0.00	1.76	-8	2	668
Farmer received **Education** from primary school (1=yes 0=otherwise)	0.34	0.48	0	1	668
Access to **Early Warning Systems** (1= yes 0= otherwise)	0.52	0.50	0	1	668
Total **Labour** per hectare used for cotton production	25.94	29.43	0	214	663
Land used for cotton production (hectares)	1.54	1.65	0	15	664
Information about the GPC environment					
GPC **helps against climate change** (1= yes 0= otherwise)	0.64	0.48	0	1	668
GPC helps with **money transfers** (1= yes 0= otherwise)	0.16	0.37	0	1	668
GPC provides **agricultural advice** (1= yes 0= otherwise)	0.12	0.32	0	1	668
Information about Climate					
Average cumulative **Rainfall** 2005-16/Average cumulative rainfall 1994-2004	1.06	0.02	1.02	1.11	668
Average **Temperature** for the rainy season over the period 2005 - 2016	34.66	0.54	33.13	35.51	668
Instrumental Variables [e]					
Number of GPC members in 2009	38.32	31.84	8	106	611
Insecticides distributed to the GPC in 2016	117.14	106.22	7	396	627

[a] Text in bold refers to the names given to the variables for the following tables.
[b] "SD" stands for "Standard Deviations".
[c] "GPC" stands for "Cotton Producers' Group".
[d] For regressions below, I substitute missing data with the mean for the age variable, that is 49.
[e] Information for instrumental variables comes from data provided by cotton companies and does not use statistics from individual surveys.

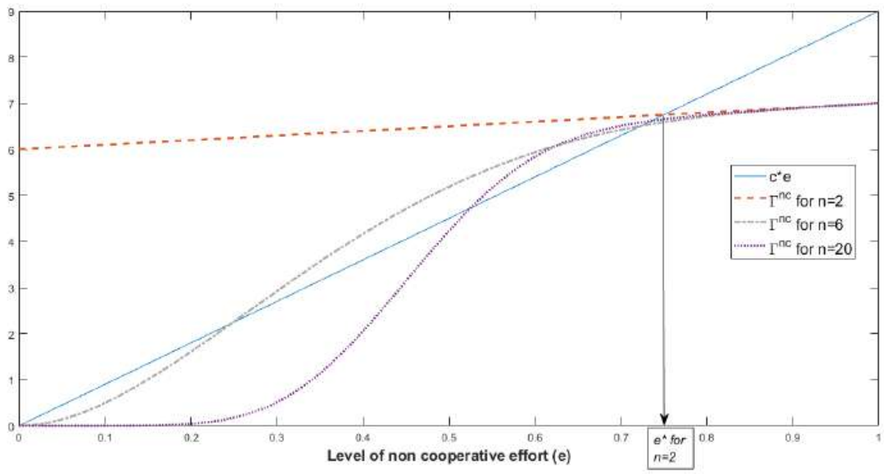

Figure 1.3: Non Cooperative equilibria of the n-player game.

Table 1.2: Classification and summary statistics for adaptation strategies

Adaptation Strategies (Dummies)	**Mean**	**Standard Deviations**
Incremental Adaptation	0.792	0.406
Soil and Water Conservation Techniques	0.626	0.484
Change in rotation of crops, including cotton	0.588	0.493
Transformational Adaptation	0.609	0.488
Migration of at least one member of the household	0.001	0.039
Increase of temporary mobility	0.003	0.055
Adoption of new crops	0.133	0.340
Stop growing some crops	0.080	0.270
Diversification to other agricultural activities	0.451	0.498
Diversification to herd breeding	0.362	0.481
Diversification to off-farm activities	0.256	0.437
Total stop of agricultural activities	0.034	0.182

Table 1.3: Regressions for Incremental and Transformational Adaptation to Climate Change

	Incremental Adaptations			**Transformational Adaptations**		
	Probit (1)	Probit (2)	Probit (3)	Probit (1)	Probit (2)	Probit (3)
Self-reported number of members	-0.005**	-0.008***	-0.014***	-0.008**	-0.009***	-0.014***
	(0.006)	(0.007)	(0.010)	(0.019)	(0.024)	(0.011)
Mean Distance	-0.010*	-0.011	-0.014	-0.016	-0.020	-0.009
	(0.006)	(0.007)	(0.010)	(0.019)	(0.024)	(0.011)
Age	0.019***	0.018***	0.016***	0.007	0.003	0.001
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
Wealth Index	-0.240***	-0.181***	-0.139***	-0.270***	-0.222***	-0.049
	(0.066)	(0.059)	(0.051)	(0.079)	(0.075)	(0.066)
Education	0.193	0.175	0.160	0.276**	0.245**	0.175
	(0.118)	(0.119)	(0.128)	(0.116)	(0.117)	(0.117)
Early Warning Systems	-0.202	-0.035	0.694**	1.035***	1.279***	1.623***
	(0.323)	(0.316)	(0.298)	(0.268)	(0.248)	(0.276)
Labour	0.001	0.002	0.003	0.008	0.009	0.005
	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.005)
Lands	0.018	0.028	0.061*	0.015	0.033	0.043
	(0.029)	(0.028)	(0.033)	(0.035)	(0.037)	(0.041)
Climate Environment:						
Rainfall Ratio		-11.709	22.020**		-32.426***	-38.859***
		(12.365)	(10.678)		(11.167)	(13.882)
Temperature		0.586***	-0.116		0.194	-0.536*
		(0.191)	(0.218)		(0.220)	(0.319)
Fixed Effect for Cotton Zone	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect for *Departements*	No	No	Yes	No	No	Yes
No. of Observations	660	660	660	660	660	660
Pseudo R^2	0.084	0.111	0.203	0.168	0.197	0.320
Marginal effects for N_h	-0.002**	-0.002***	-0.002***	-0.003**	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Standard errors clustered at village level in parentheses. Constant terms are not reported. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Probit (1) introduces results for the simplest probit regression with household characteristics and cotton zone fixed effects. Probit (2) introduces climate variables. Probit (3) corresponds to the model with *departements* fixed effects.

Table 1.4: Regressions with instrumental variables for Incremental and Transformational Adaptation to Climate Change

	Incremental Adaptations			**Transformational Adaptations**		
	Instrument (1)	Instrument (2)	Both	Instrument (1)	Instrument (2)	Both
Second stage:						
Self-reported number of members	-0.021***	-0.012***	-0.013***	-0.022***	-0.010**	-0.011**
	(0.005)	(0.003)	(0.003)	(0.007)	(0.005)	(0.005)
First stage:						
Amount of insecticides	0.157**		0.048**	0.157**		0.043*
	(0.070)		(0.023)	(0.070)		(0.023)
Size of GPC in 2009		1.041***	0.967 ***		1.041***	0.977***
		(0.081)	(0.086)		(0.081)	(0.083)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effect for Cotton Zone	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	622	606	606	622	606	606
Marginal effects for N_h	-0.021 ***	-0.012***	-0.013***	-0.022***	- 0.010**	-0.011**
	(0.005)	(0.003)	(0.003)	(0.006)	(0.005)	(0.005)
chi2(1)	12.13	5.81	11.22	5.28	0.02	0.27
prob > chi2	0.001	0.016	0.001	0.022	0.877	0.604

Standard errors clustered at village level in parentheses. Constant terms are not reported. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Instrument (1) corresponds to the estimation with the quantity of insecticides as unique instrumental variable. Instrument (2) only uses the size of GPC back to 2009 as instrumental variable. The last specification jointly analyses the two instrumental variables. Chi2 refers to the Wald test of the exogeneity of the instrumented variables. If the test statistic is not significant, there is not sufficient information in the sample to reject the null hypothesis of no endogeneity. The results include some estimates from the first stage regression to assess how strongly the instruments are correlated with the size of the cooperative.
Control variables are still the following: mean distance, age, wealth index, education, early warning systems, land area, labour, rainfall and temperature.

Table 1.5: Results of two interaction models with GPC characteristics

	Incremental Adaptations		**Transformational**
	Total	SWC	**Adaptations**
Money Transfers x Help against climate change x N_h	-0.021	-0.030**	-0.048***
	(0.016)	(0.013)	(0.016)
Agricultural advice x Help against climate change x N_h	0.064***	0.203***	0.038***
	(0.020)	(0.013)	(0.011)
All constitutive terms	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Fixed Effect for Cotton Zone	Yes	Yes	Yes
Fixed Effect for *Departements*	Yes	Yes	Yes

Standard errors clustered at village level in parentheses. Constant terms are not reported. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. GPC stands for "Group of Cotton Producers". SWC stands for "Soil and Water Conservation Techniques". Control variables are still the following: mean distance, age, wealth index, education, early warning systems, land area, labour, rainfall and temperature. "N_h stands for the self-reported number of members in the cooperative. The two variables displayed here are the final results from two separate regression models detailed in appendices A1 and A2.

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Chapter 2

Index insurance and agricultural decisions: assessing the external validity of multiple randomized controlled trials

This chapter is joint work with Jules Gazeaud (J-PAL MENA).

2.1 Introduction

Farm incomes are highly vulnerable to weather shocks, especially in developing countries where rainfed agriculture is still the norm (Rockström and Falkenmark, 2015) and access to formal insurance is extremely limited (Hazell, 1992; Alderman and Haque, 2007; Mahul and Stutley, 2010). To self-insure against risk, farmers routinely employ a variety of risk-management strategies such as income diversification and the use of low-risk/low-return production technologies (Rosenzweig and Binswanger, 1992; Morduch, 1995; De Janvry and Sadoulet, 2001; Dercon and Christiaensen, 2011). These strategies are often considered as too conservative because they can hamper productivity gains (Dercon, 2005) and therefore industrialization (Gollin et al., 2002).

It is against this background that index insurance has been promoted as a major innovation to protect farmers against adverse shocks and increase productive investments (Alderman and Haque, 2007; Mahul and Stutley, 2010). Unlike traditional insurance that pays individual farmers based on the losses they experience in their fields, index insurance compensates based on an index that is designed to be highly correlated but not identical to farmer losses. This type of insurance is particularly appealing because it typically reduces transaction costs and concerns about moral hazard and adverse selection. Interventions offering index insurance products to farmers have rapidly spread in developing countries. For example, Carter et al. (2017, p.423) estimate that "*more than 15 developing countries have offered individual-level index insurance schemes, sometimes at a massive scale, and some 20 have offered it at the institutional or geographical level*".

A growing and now meaningful evidence base suggests that index insurance can successfully help farmers to cope with weather shocks and foster the adoption of more productive technologies (see e.g. Karlan et al., 2014; Carter et al., 2018; Janzen and Carter, 2018; Hill et al., 2019). While such studies are commendable for the care with which they estimate impacts, critics often point out that their results lack external validity (Rodrik, 2009; Deaton, 2010; Deaton and Cartwright, 2018). Each study is indeed rooted in a particular context, and although it can give internally valid estimates, it is not clear whether these estimates are informative about impacts in other contexts (Pritchett and Sandefur, 2015).

The aim of this paper is to provide inputs to gauge the external validity of index insurance experiments. Specifically, we use a Bayesian hierarchical model to aggregate data from six experiments that look at index insurance effects on production decisions. The Bayesian hierarchical model offers an appealing statistical tool, not only to disentangle heterogeneity in treatment effects from pure sampling variation, but also to estimate the average impact of index insurance and explore the potential sources of heterogeneity.

Our focus on farmer production decisions is motivated by three reasons. First, impacts are theoretically ambiguous. While index insurance could allow more risk-taking, the need to pay early premiums and the lack of financial resources of farmers could in fact crowd-out productive investments (Giné and Yang, 2009), especially in contexts with deficient credit market. Second, this question is well-tailored to the current policy debate. Demand for index insurance is price sensitive and particularly low at market prices (Cole et al., 2013; Jensen and Barrett, 2017; Cai et al., 2020). The optimal level of subsidies remains unclear and crucially depends on the size of the productivity gains at stake. Third, although the overall evidence suggests that index insurance can stimulate risky production decisions, some heterogeneity exist across studies and deserve to be investigated more systematically.[1] We used three inclusion

[1]We could have focused on two related strands of the literature on index insurance: the ex-post impacts on household welfare; the determinants of demand. However, we view these aspects as less suited for the kind of systematic analysis we will conduct. On the one hand, ex-post impacts of index insurance are not expected to be generalizable since they typically depend on idiosyncratic shocks

criteria to define the set of relevant studies for this project: (i) the study should consist of an increase in access to index insurance; (ii) the study should be designed as a randomized controlled trial; (iii) the study should measure impacts on farmer production decisions. Overall, we identified ten studies satisfying our inclusion criteria and were able to obtain data from six: Elabed and Carter (2014), Karlan et al. (2014), Cole et al. (2017), Bulte et al. (2019), Hill et al. (2019), and Stoeffler et al. (2021). Together, these studies cover a large set of regions and countries (Bangladesh, Burkina Faso, Ghana, Kenya, India and Mali), evaluate a reasonable spectrum of index insurance products, and thus offer an excellent opportunity to investigate external validity.

We examine the effects of index insurance on five main outcomes: the amount of cultivated area, fertilizers, pesticide, seeds, and an index of crop portfolio riskiness. These outcomes are constructed using original data from each study. We focus on intention-to-treat effects – that is the effect of being offered insurance regardless of the final decision to subscribe – because it is arguably the most relevant parameter for a policymaker interested in the economy-wide consequences of index insurance programs. To improve our understanding of the drivers of heterogeneity in treatment effects, we examine the following covariates: household wealth, household size, household head age, literacy, and predicted outcomes. This helps us to assess the characteristics that are associated with larger and more heterogeneous effects, and can help to generate important targeting implications for insurance interventions.

This paper makes two main contributions. First, it informs the policy debate as to whether and how to introduce index insurance products. Index insurance triggered a considerable interest and has recently been described as one of the most important current opportunities to help developing countries to "*achieve the goal of increased investment in agriculture, accelerated growth, and poverty reduction*" (Carter et al., 2017, p.424). Using a Bayesian hierarchical framework and existing data from six randomized controlled trials, we quantify both the average impact of index insurance on farmer production decisions and the degree of external validity of the results. We focus on five production decisions, one of which – an index of crop portfolio riskiness – has been somewhat neglected by existing studies. We also look at six potential sources of heterogeneity in treatment effects, which helps to identify whether there are subgroups for which insurance is particularly effective. In sum, this paper provides crucial evidence for future index insurance interventions, not only to better predict their likely impacts on production decisions, but also to improve their targeting and achieve bigger impacts.

(Rosenzweig and Udry, 2020). On the other hand, studies on the determinants of demand look at very different dimensions such as the level of subsidy and the presence of add-on interventions to increase trust, financial literacy, or risk-sharing (see e.g. Cole et al., 2014; Dercon et al., 2014; Cai et al., 2015; Stein, 2018; Belissa et al., 2019). It is not clear on which dimension we should focus. For recent reviews on both aspects, see Marr et al. (2016); Carter et al. (2017); Jensen and Barrett (2017).

The second contribution is to the literature on external validity, open science, and research transparency. Empirical studies, and particularly randomized controlled trials, are often criticized on the basis that their results are drawn from specific contexts and may therefore lack external validity (Peters et al., 2018; Ravallion, 2018). A rapidly growing literature relies on Bayesian hierarchical models to aggregate information from multiple settings and estimate external validity (Hsiang et al., 2013; Burke et al., 2015; Meager, 2016; Bandiera et al., 2016; Vivalt, 2019; Meager, 2019; Romero et al., 2020; Dehejia et al., 2021; Jackson and Mackevicius, 2021). We add to this body of literature by applying the method to a new question, and, perhaps more importantly, by showing the scope for preregistration when data are not publicly available. Study preregistration is one of the most popular tools to promote open science and research transparency (Olken, 2015; Christensen et al., 2019). It allows researchers to bind their hands against data mining (Humphreys et al., 2013; Brodeur et al., 2016), and to mitigate publication bias arising from the under-report of null results (Casey et al., 2012; Chambers and Tzavella, 2020). Yet, preregistration remains largely confined to experimental studies which in turn constitute only a small share of the overall economic research (Burlig, 2018). An important innovation of our work is that we preregistered all our analysis prior to having the data at hand. This paper thereby illustrates how preregistration can be credibly implemented by third-party researchers when data are already collected but not deposited in public repositories.

The rest of the paper is organized as follows. Section 2.2 discusses study selection. Section 2.3 describes the data. Section 2.4 presents the methodology. Section 2.5 outlines the results.

2.2 Study Selection

2.2.1 Inclusion criteria

We restrict our analysis to studies that (i) increase farmer access to index insurance, (ii) are designed as randomized controlled trials, and (iii) measure impacts on production decisions. To maximize the number of eligible studies and limit potential publication biases, we did not restrict the set of studies to published articles. Since index insurance is a relatively new product, we did not impose particular time constraints either. Overall, we found ten studies satisfying our inclusion criteria. In order to identify eligible studies, we relied first on the studies listed in J-PAL et al. (2016)'s review. We found an initial set of four eligible papers: Mobarak and Rosenzweig (2013); Elabed and Carter (2014); Karlan et al. (2014); Cole et al. (2017). We then relied on Google Scholar searches to screen all studies citing at least one of these four initial papers, and we further assessed their eligibility by reviewing their title, abstract, and empirical analysis. This resulted in the inclusion of three additional papers: Berhane et al. (2015); Ahmed et al. (2017); Stoeffler et al. (2021). We completed this search process in April 2018. Three additional papers reached our attention between that date and March 2019 – Belissa and Marr (2018); Bulte et al. (2019); Hill et al. (2019) – bringing the total to ten papers. We stopped screening potential papers to include in this research project in June 2020, following the registration of our pre-analysis plan.

2.2.2 Data request

Before the registration of our pre-analysis plan, we contacted the authors of each paper to present our project and to know whether they would accept to share the underlying data. We received principle agreements for seven studies.[2] Importantly, at this stage, although the authors already agreed to share their data for our project, we made clear that our first step would be to preregister our study and that we therefore only needed their survey instruments to start the project. Once we registered our pre-analysis, we followed-up with the authors of each study and obtained the data for six of the seven studies for which we received principle agreements (for the remaining study, the authors were too busy because of Covid-19 to prepare and send us the required data).

2.2.3 Description of the studies

Together, the six studies cover a large set of regions and countries (Bangladesh, Burkina Faso, Ghana, Kenya, India and Mali). Five studies have been published in peer-reviewed journals. The remaining is available as unpublished mimeos as of June 2021. Further characteristics of the studies are provided in Table 2.1. We report information on studies' start year, experimental design, eligibility criteria, sampling frame, sample size, and number of clusters. Start years range from 2009 in Ghana to 2016 in Kenya. Of the six studies, four are designed as price experiments. Price experiments randomly assign different levels of premium subsidies to treated clusters. Depending on the studies, clusters are villages, farmer groups or cooperatives. Other studies provide free index insurance with randomization occurring at the household level. Two studies have additional treatments: Karlan et al. (2014) cross-randomize cash grants; Cole et al. (2017) cross-randomize coupons for discounts on locally appropriate inorganic fertilizer. Eligibility criteria vary largely across studies. Cole et al. (2017) target land owners, Karlan et al. (2014) target maize cultivators with less than 15 acres of land, and Hill et al. (2019), Stoeffler et al. (2021), Bulte et al. (2019), and Elabed and Carter (2014) target individuals belonging to specific groups (NGOs, farmer

[2] These studies are: Mobarak and Rosenzweig (2013), Elabed and Carter (2014), Karlan et al. (2014), Cole et al. (2017), Bulte et al. (2019), Hill et al. (2019), and Stoeffler et al. (2021). For three studies (Berhane et al., 2015; Ahmed et al., 2017; Belissa and Marr, 2018), either data were not shareable or we received no answer. Since our meta-analysis methodology requires original data, we do not include them in this study.

groups, cooperatives). Broadly speaking, however, these studies all cover smallholder farmers residing in specific regions of low- or middle-income countries (as can be inferred from the sampling frames). All but one study have a baseline survey. Sample sizes vary from 780 in Kenya to 2,300 in Bangladesh. Interestingly, studies with the largest sample size are not those with the highest number of clusters. Because clusters and sample size are two of the main parameters that researchers can influence to achieve desired statistical power, this could reflect the fact that all studies maximize the same power calculation function under different budgetary and practical constraints.

2.2.4 Description of the insurance products

Table 2.2 describes the different index insurance products offered across studies. Of the six products, three are based on rainfall, two are based on area-yields, and one is hybrid (that is, based both on rainfall and area-yields). In four studies, the products are explicitly targeted towards particular crops: Elabed and Carter (2014) and Stoeffler et al. (2021) target cotton production; Karlan et al. (2014) target maize production; Bulte et al. (2019) target four crops (soya bean, sorghum, sunflower, and maize). In other studies, the products are not crop-specific. Large disparities exist in sale prices, both within and across studies. Within study disparities are due to the price experiment design of four studies. Disparities across studies reflect only to some extent differences in actuarially fair prices. Insurance purchase was generally an individual decision, except in Elabed and Carter (2014) and Stoeffler et al. (2021) where farmer groups collectively decided to purchase the insurance. In most studies, the amount of insurance that farmers could purchase depends on the amount of land they cultivate. A notable exception is the study India Cole et al. (2017), which offered insurance products as stand-alone policies: treated households received 10 policies. Take-up of the different products vary from 29% in Mali to 100% for the products offered for free. Payoff triggers vary across studies and depend for example on the amount of dry/wet days, on the duration of dry spells, on cumulative rainfall, or on area yields averages. While products based on rainfall typically use data from weather stations, area-yield products rely upon data from crop-cutting exercises or from purchasing companies.

2.3 Data

2.3.1 Primary outcomes

We focus on five main outcomes: the amount of cultivated area, fertilizers, pesticides, seeds, and an index of crop portfolio riskiness. Outcome choices are guided by both theoretical and practical considerations. Theoretically, a well-established theory of change outlines that insurance provision could either increase or decrease farmer risk-taking depending on financial constraints and risk preferences.[3] We therefore focus on production decisions involving a certain degree of risk-taking. Practically, because our empirical framework requires outcomes to be measured in similar ways across studies, the choice is constrained by data availability. We were interested to also analyze outcomes such as loan subscription, irrigation, and labor expenditures. However, these outcomes are either missing in many studies or measured in very inconsistent ways. We therefore limit our analysis to the five following outcomes (as specified in our pre-analysis plan): the amount of cultivated area, fertilizers, pesticides, seeds, and an index of crop portfolio riskiness – available for all studies and measured fairly consistently.

Most of these outcomes have straightforward definitions. A notable exception is the index of crop portfolio riskiness. We draw on Gehrke (2019) and define this index for household i as $R_i = \sum r_m k_{im} / \sum k_{im}$, where r_m is the coefficient of variation of the yield of crop m, and k_{im} is the amount of land devoted by household i to the cultivation of crop m. Our definition differs from Gehrke (2019) in three ways. First, we rely on the allocation of cultivated areas to each crop instead of the allocation of other inputs such as fertilizers. We view the allocation of land as perhaps more appropriate because more ex-ante with respect to rainfall realization, and because different crops may have different fertilizer needs.[4] Second, while Gehrke (2019) uses production data in six Indian districts over the 1998-2012 period, we mainly use data measured at the national level and available over a larger time span (1961-2017).[5] Third, for studies in which the insurance products are based on rainfall exclusively (see Table 2.2), we enrich the index with the term f_m to take into account the rainfall sensitivity of crop m. The idea is to prevent the influence of other production risks, such as pests or diseases, which are not covered by rainfall insurance. We use monthly rainfall data drawn from the Climatic Research Unit (Harris et al., 2014; Santoni, 2019), and simply define f_m as the correlation between total rainfall over the three wettest months and the yield of crop m. As a robustness check, we also add a quadratic term to take into account the possibility of non-linear relationship. Overall, this index captures how insurance provision affects farmer crop portfolio choices in light of the traditional risk-productivity trade-off outlined in the literature – an aspect relatively neglected

[3] For recent theoretical models of investment decisions under financial and risk constraints, see for instance Karlan et al. (2014) and Gazeaud et al. (2021).

[4] The data set used by Gehrke (2019) does not include information on the allocation of land to the different crops, which may explain her focus on other inputs.

[5] In particular, we rely on time series of agricultural yields provided by the FAO (FAOSTAT provides annual statistics on harvested areas, production quantities and yields for 173 crops over the 1961-2017 period, covering production of all primary crops for all countries – see http://www.fao.org/faostat for more details). For India, given the possibly large disparities in crop riskiness across regions, we use sub-national data from the Directorate of Economics and Statistics, Ministry of Agriculture – see https://aps.dac.gov.in/ for more details. To our knowledge, India is the only country in our sample providing yearly sub-national crop production statistics.

by previous studies.

In Table B1, we provide more details on how the outcomes have been derived, and which survey questions have been used in each study.[6] While all outcomes are measured over the rainy season, Hill et al. (2019) also measured outcomes over the dry season. We prefer to focus exclusively on outcomes over the rainy season because data over the dry season are incomplete, insurance products only cover the rainy season, and payouts for the rainy season could influence production decisions over the dry season (for example, in Bangladesh, rainy season payouts coincided with the planting of dry season crops). Naturally, outcomes are not measured in the exact same ways across studies. For example, some studies collect fertilizer expenditures, while others collect only purchased quantities. We therefore standardize all outcomes. Finally, to deal with outliers, we winsorize outcomes at the 99th percentile.

2.3.2 Covariates of interest

Household-level covariates may be particularly helpful to understand what drives the heterogeneity in treatment effects. In addition, they may provide useful evidence to guide the targeting of insurance products and identify subgroups for which index insurance is particularly effective. For example, using seven experimental evaluations of micro-credit effects, Meager (2019) finds that micro-credit only affected the profits of households with prior business experience, and that the effects for this subpopulation vary largely across contexts. This pattern suggests that business experience of micro-credit beneficiaries is a necessary but not sufficient condition for positive effects. However, because of a lack of baseline data in the micro-credit studies, Meager (2019) limits her analysis to business experience. In our case, we can potentially investigate a much larger set of dimensions because baseline data are available in all but one studies.

We examine the following covariates: a wealth index, household size, age, literacy, and predicted outcomes.[7] For continuous covariates, we divide households in two groups with respect to their mean (stratifying by studies). We derive the wealth index using the methodology developed by the Demographic and Health Survey (DHS) Program. We predict each of our five outcomes using the repeated split sample (RSS) procedure developed by Abadie et al. (2018). We use 100 repetitions and the following set of predictors measured at baseline: chemicals usage, cultivated area, land ownership, household head gender, literacy, education, age (and age^2), household size, wealth, livestock, bank account, distance to rainfall station, experience of past weather shocks, and risk preferences.[8]

[6] All this information as been specified in our pre-analysis plan

[7] We also specified in our pre-analysis plan that would analyze household head gender, but very few households are in fact headed by female, as shown in Table 2.3.

[8] In practice we first regress each outcome on predictors using the full sample of controls, and

Table B2, taken from our pre-analysis plan, specifies the data that we used to derive each covariates in each study. We note that the list of variables available to construct the wealth index and the predicted outcomes vary somewhat between studies. This should not be an issue since our main purpose is to identify groups with high and low levels of wealth and predicted outcomes within each studies. In a few cases, information is only available at endline. While we can legitimately rely on endline data for predetermined characteristics such as the age, gender or literacy of the household head, it may be misleading for variables potentially affected by the treatment. To predict outcomes we focus only on variables measured at baseline or predetermined. For the wealth index, we exclude livestock and focus on highly autocorrelated and relatively illiquid outcomes such as televisions, materials used for housing construction, and types of water access and sanitation facilities. Table 2.3 shows the descriptive statistics for the pre-specified covariates and predictors and discloses substantial heterogeneity in individual characteristics across studies. If treatment effects vary by subgroups of households along these covariates, the prevalence of subgroups in each study may generate heterogeneity in treatment effects.

Although it would be interesting to investigate heterogeneity in treatment effects using study-level covariates such as the characteristics of the insurance products, for two reasons we prefer to leave it to future research. First, with only six studies and no within-study variation, the sample size would be particularly limited for such analysis. Second, some of the covariates of interest are perfectly colinear and therefore impossible to disentangle. Insurance may be more attractive to farmers if products are provided at the group level (De Janvry et al., 2014) or if premiums are paid after harvest (Casaburi and Willis, 2018). We could therefore be tempted to look at dimensions such as the decision level of take-up (group vs. individual) or the timing of payment (up-front vs. at-harvest). However, looking at Table 2.2, we see that only the insurance products in Burkina Faso and Mali have been offered at the group level, or using a pay-at-harvest contract, meaning that these two characteristics are not separable – the Burkina Faso and Mali products are also the only two targetting cotton and based on area-yields.

A promising avenue to investigate heterogeneous effects with respect to product characteristics is to randomly vary product characteristics among targeted populations, such as in Casaburi and Willis (2018). In this study, we focus on the subset of projects designed as price experiments and explore heterogeneous effects with respect to assigned prices (see Table 2.1).

then use the coefficients from this regression to generate predicted outcomes without treatment for all sample units.

2.4 Methodology

This section summarizes the Bayesian hierarchical model we use to estimate the external validity of the studies described in Section 2.2. Our approach closely follows Gelman et al. (2013), Bandiera et al. (2016), and Meager (2019), to which we refer readers for further technical details.

We are interested in the effect of a randomly-assigned increase in access to index insurance on the set of agricultural decisions described in Section 2.3.1. A natural starting point is the following simple descriptive model:

$$y_{ik} = \mu_k + \tau_k T_{ik} + \epsilon_{ik} \tag{2.1}$$

where T_{ik} is a dummy equal to one if household i in study k is offered index insurance; τ_k is the treatment effect and the parameter of interest of each study k; μ_k is the mean outcome in the control group in study k; and ϵ_{ik} is the error terms (clustered at the level of treatment, that is the household or the village depending on the study). We standardize all outcome variables because they are typically measured using different scales or units across studies.[9] Note that τ_k corresponds to the intention-to-treat effect of index insurance, that is the effect of being offered index insurance regardless of take-up decisions. This parameter is of particular interest for policymakers who need insights on the potential economy-wide consequences of index insurance programs.

We define the *true* heterogeneity in treatment effects as $\sigma_\tau^2 = var(\tau_k)$. This quantity provides a natural measure to gauge the level of external validity of available evidence. The main challenge, however, is that parameters $\{\tau_1, \tau_2, ..., \tau_K\}$ are generally unknown, and one can only observe estimates $\{\hat{\tau_1}, \hat{\tau_2}, ..., \hat{\tau_K}\}$. Importantly, $var(\hat{\tau_k})$ not only reflects the true heterogeneity in treatment effects across studies σ_τ^2, but also sampling variation (sometimes also called idiosyncratic or statistical variation, that is the difference between $\hat{\tau_k}$ and τ_k resulting from the use of sampling techniques).[10] In other words, because of sampling variation, the observed heterogeneity $var(\hat{\tau_k})$ overestimates the true heterogeneity σ_τ^2.

2.4.1 The hierarchical model

The hierarchical model offers an appealing statistical tool, not only to disentangle σ_τ^2 from sampling variation, but also to estimate the average impact of index insurance τ and explore the potential sources of heterogeneity. This model combines the

[9] The standardized value of outcome y for household i in study k is defined as $\tilde{y}_{ik} = (y_{ik} - \bar{y}_k)/\bar{\sigma}_k$, where $\bar{y}_k$ and $\bar{\sigma}_k$ are the mean and standard deviation in the control group.

[10] Because of the experimental design of each study, we assume no systematic bias in estimates $\hat{\tau_k}$.

available evidence in a structured way and is particularly suited to situations where data from multiple experimental studies are available (Andrews and Oster, 2019). In contrast with classical meta-analysis techniques (often referred to as the fixed-effect or pooling model), which consider that individual studies estimate a common effect, the hierarchical model allows for the presence of heterogeneous effects across studies. Because index insurance studies have been conducted in contexts that differ systematically from each others (see Tables 2.1 and 2.2 above), this model is expected to be more appropriate. This approach to data aggregation was first pioneered by Rubin (1981). The typical set-up specifies that each individual study estimates its own treatment effect τ_k, and that each individual τ_k is in turn drawn from a common distribution. It can be described as follows:

$$\begin{aligned} \hat{\tau_k} &\sim N(\tau_k, \hat{se}_k^2) \\ \tau_k &\sim N(\tau, \sigma_\tau^2) \end{aligned} \tag{2.2}$$

where $\hat{\tau_k}$ and $\hat{se}_k^2$ are estimates of the treatment effect and sampling error in each individual study, and τ_k, τ and σ_τ^2 are defined as above. The first line of model (2.2) assumes that each individual $\hat{\tau_k}$ is a good estimate of its own study-specific treatment effect τ_k (a fairly reasonable assumption given the experimental design of the studies and the relatively large samples). The second line of model (2.2) assumes that treatment effects $\{\tau_1, \tau_2, ..., \tau_K\}$ are normally distributed around τ and σ_τ^2. This assumption ensures that the model recovers the results of classical meta-analysis if there is no heterogeneity in treatment effects ($\sigma_\tau^2 = 0$), and the results of initial studies if there is considerable heterogeneity in treatment effects ($\sigma_\tau^2 \rightarrow \infty$) (Meager, 2019). An additional assumption for the estimation of model (2.2) is that of exchangeability: the joint distribution of $\{\tau_1, \tau_2, ..., \tau_K\}$ should be invariant to permutations of the K indices (Diaconis, 1977). This means that nothing else than the data could help to distinguish one study from another.

We follow Meager (2019) and incorporate more structure to model (2.2) by using the original data from each study rather than just the reported estimates. The use of original data has at least two advantages. First, as noted earlier, it allows us to standardize outcomes and to construct variables that were not analyzed in the original studies. Second, original data allow us to incorporate household-level covariates in the model and thereby to explore the potential sources of heterogeneity across studies. The hierarchical model with and without household-level covariates is presented in Appendix B.

2.4.2 Bayesian estimation

In model (2.2), only $\hat{\tau}_k$ and $\hat{se}_k^2$ are observable. Other parameters τ_k, τ, σ_τ^2 are unknown and should be estimated. In line with the recent literature, we use a Bayesian estimation method. The Bayesian methodology considers τ and σ_τ^2 as random variables and combines existing evidence with information from outside the data (the so-called "priors") to jointly estimate posterior distributions.[11] Technical details are provided in Appendix B.

In practice, we conduct inference using the *baggr* (short for "Bayesian aggregator") package – an *R* package designed by Rachael Meager and Witold Wiecek with the objective of facilitating the implementation and tractability of Bayesian meta-analysis (Meager and Wiecek, 2020). [12] By default, priors are automatically chosen based on the data brought to the model. However, it is also possible to specify priors such that theoretical and contextual insights are reflected in the model. Providing informative priors can greatly improve the precision of inference (Chung et al., 2013). However, the risk is to introduce bias if priors are poorly informed. According to Meager (2019), when the number of studies is small, as is the case in this paper, precision rather than bias should be the main concern. We therefore choose to specify priors. We show that results are robust to using the default, data-driven priors obtained from the *baggr* package (see Figures B1, B2, and B4).

To complete the Bayesian hierarchical model, we specify the following set of priors for the hypermean τ and the hyper-standard-deviations σ_τ:

$$\begin{aligned} \tau &\sim N(0, 100^2) \\ \sigma_\tau &\sim Cauchy(0, 5) \end{aligned} \tag{2.3}$$

2.5 Results

We use the Bayesian hierarchical model described in the previous section to provide evidence on (i) the average effect of index insurance, (ii) the degree of heterogeneity in effects, (iii) the potential sources of heterogeneity in effects, and (iv) the predicted effect of index insurance in a new study.

[11] This estimation method has several advantages compared to frequentist alternatives. Frequentist alternatives include methods such as empirical Bayes and maximum likelihood. See Meager (2019) for a summary of why Bayesian inference is preferable for data aggregation when the number of studies is limited. In short, Bayesian inference can reduce mean squared error and the risk of overfit.

[12] As specified in our pre-analysis plan, we initially selected the package for its "mutau" model designed to incorporate data on the control group's mean outcomes and the uncertainty on those. However, the standardization of the outcomes performed during data processing prevents any variance in the control group's means and leads the "mutau" model to fail in *baggr*.

2.5.1 The average effect of index insurance on production decisions

We first present evidence on τ, the average effect of index insurance on farmer production decisions. Estimates of τ provide important indications on the likely effect of index insurance in contexts that are comparable to the current set of contexts. Figure 2.1 shows for all the outcomes described in Section 2.3.1 the posteriors obtained from the Bayesian hierarchical model as well as the estimates from the pooling model for comparisons. We find strong evidence from the pooling model that households offered index insurance cultivate more land and invest more in productive inputs. The average amount of cultivated land is 0.09 standard deviations higher for beneficiary households ($p = 0.013$). Households that were offered index insurance use also more seeds (+0.10 SD), more pesticide (+0.09 SD), and more fertilizers (+0.07 SD). The effect on the index of crop riskiness is positive but much smaller and not statistically significant.

Estimates from the Bayesian hierarchical model confirm that the effect of index insurance on production decisions is likely positive. The posterior means of τ are positive for all outcomes and similar to the estimates from the pooling model. However, posterior distributions suggest that effects are more uncertain than in the pooling model and may be close to zero in some cases. All but one 95% posterior intervals include zero, and, for some outcomes, there is a small probability of negative effects. The 95%-interval is [−0.03 SD, +0.24 SD] for cultivated area, [−0.08 SD, +0.09 SD] for the crop riskiness index, [−0.05 SD, +0.23 SD] for fertilizers, [0.00 SD, +0.16 SD] for pesticide, and [0.00 SD, +0.21 SD] for seeds. Results are very similar using the automatic priors (Figure B1).

Overall, these results show that index insurance has the potential to foster the productive investments of farm households but that effects are more uncertain than suggested by the pooling model. The pooling model can be misleading because it considers that there is no genuine variation in impacts across studies (which may lead to underestimate the uncertainty around treatment effects). Index insurance studies have been conducted in contexts that differ dramatically from each others. The Bayesian hierarchical model offers a convenient framework to detect heterogeneity in treatment effects and take into account this heterogeneity while estimating the average effect of index insurance.

In what follows, we use the Bayesian hierarchical model to provide more systematic evidence on the true degree of heterogeneity in treatment effects across studies, to explore the possible sources of this heterogeneity, and to predict the likely effect of index insurance in a new context.

2.5.2 The heterogeneity in treatment effects

Figure 2.2 shows the posteriors of study-specific treatment effects τ_k as well as the no-pooling OLS estimates. While most point estimates suggest positive effects, there is considerable heterogeneity in the no-pooling estimates. For example, estimates for cultivated land vary from a minimum of −0.05 SD in Burkina Faso to a maximum of +0.44 SD in Ghana. The 95% confidence intervals also vary largely: from [−0.32 SD, +0.23 SD] in Burkina Faso to [+0.22 SD, +0.67 SD] in Ghana. It is important to note, however, that these variations not only reflect the true heterogeneity in treatment effects across studies but also random variations due to sampling errors. The Bayesian hierarchical model allows to separate the genuine heterogeneity in treatment effects from the sampling variation. It is therefore not surprising that in Figure 2.2 BHM estimates display less variations than OLS estimates. However, substantial differences persist across studies. For example, the posterior means for cultivated area vary from −0.01 SD in Burkina Faso to +0.29 SD in Ghana – the corresponding 95% posterior intervals are [−0.13 SD, 0.09 SD] and [+0.09 SD, +0.53 SD]. Overall, these results suggest that τ_k is heterogeneous across studies and that pooling the data across studies to estimate a common treatment effect (as done in classical meta-analysis) is rather dubious. The Bayesian hierarchical model offers a more reasonable framework.

We now use evidence on σ_τ^2, the true heterogeneity in treatment effects across studies, to derive metrics to gauge the extent of external validity of index insurance experiments. If $\hat{\sigma}_\tau^2$ is close to zero, there is almost no heterogeneity across studies and $\hat{\tau}$ provides a better estimate of each τ_k than its corresponding $\hat{\tau}_k$ – external validity is high. Alternatively, if $\hat{\sigma}_\tau^2$ is large, the heterogeneity across studies is important and each $\hat{\tau}_k$ provides a better measure of its corresponding τ_k – external validity is low. An important question, however, is that of what constitutes a large or small value of $\hat{\sigma}_\tau^2$. To interpret the magnitude of $\hat{\sigma}_\tau^2$, a range of pooling metrics have been developed, the most prominent of which is perhaps the pooling factor (Gelman and Hill, 2006). The pooling factor is defined by Box and Tiao (1973) as $\lambda_k = \hat{se}_k^2/(\hat{se}_k^2 + \hat{\sigma}_\tau^2)$. The main advantage of the pooling factor is that it has a relatively straightforward interpretation. In particular, the potential values of λ_k are restricted to the interval $[0,1]$, and values above 0.5 indicate a dominance of sampling variation over treatment effect heterogeneity. For each outcome, we report $\lambda(\tau)$, the pooling factor averaged across all studies, which corresponds to the percentage of total variation in treatment effects attributable to sampling variation. We also report evidence on a complementary metric, the generalized pooling factor (Gelman and Pardoe, 2006). [13]

Table 2.4 shows large differences depending on the outcome considered, with only 27% of the observed variation in treatment effects due to sampling variation for cultivated area or fertilizers, against 61% for the index of crop riskiness. Averaged across all outcomes, we find limited pooling of information across studies: 42%

[13] More details on these metrics are provided in Appendix B.

of the observed variation in treatment effects is attributable to sampling variation. This contrasts with the results of Meager (2019) who derived a pooling factor of 60% across seven micro-credit experiments. This relatively low level of pooling in our set-up helps to understand why in Figure 2.1 the BHM posteriors of τ display more uncertainty than the pooled estimates, and why substantial differences subsist in the BHM estimates of τ_k in Figure 2.2 (especially for outcomes with small pooling factors: cultivated area, fertilizer, and seeds). Overall, this suggests that index insurance generates effects that are fairly heterogeneous across contexts.

2.5.3 The sources of heterogeneity in treatment effects

We look at five household-level covariates that could help to explain the heterogeneity in treatment effects across studies: a household wealth index, household size, household head age, household head literacy, and household predicted outcome. We define dummy variables equal to one if the age of the household head is above average, if the head is literate, if the wealth index is above average, if the household size is above average, and if the predicted outcome is above average.[14] For each outcome and each covariate, we report in Figure 2.3 the posteriors of the average effect of index insurance for the group with the covariate equals to zero as well as the additional effect for the group with the covariate equals to one. In addition, using the four studies designed as price experiments (Table 2.1), we report the effect of receiving insurance offers at a price below average vs. at a price above average.

The results show limited heterogeneity along the covariates we study (Figure 2.3). We find some evidence that treatment effects are higher for households with low levels of predicted outcomes. The effect of index insurance on cultivated area is 0.10 SD higher for households who would have cultivated less land in the absence of index insurance offers. Similarly, the effect of index insurance on pesticide is 0.11 SD higher for households who would used less pesticide in the absence of index insurance offers.[15] Treatment effects also seem larger among the worse-off households (in terms of the wealth index) and among households offered a low price for the index insurance product – but predictive distributions include zero comfortably for both of these covariates. Results for household head age, household head literacy, and household size display little heterogeneity.

2.5.4 The predicted effect of index insurance in a new study

We use estimates from the Bayesian hierarchical model on σ_τ^2 to predict the effect of index insurance in a new context (τ_{k+1}). Figure 2.4 reports the posterior means and

[14] See Section 2.3.2 for more details.
[15] This heterogeneity is visible across all the studies (Figure B3).

intervals of τ_{k+1} as well as the estimates from the pooling model for comparisons. Overall, we find very uncertain predicted effects.[16] The posterior intervals of τ_{k+1} are considerably wider than the confidence intervals from the pooling model, reflecting the sizeable heterogeneity in treatment effects documented in Section 2.5.2, especially for outcomes with the largest heterogeneity (seeds, fertilizers and cultivated area). If we were to run a new experiment, the chances of obtaining null or negative effects would be non-negligible. For example, the treatment effect on cultivated area has a 50% chance of being between 0.00 SD and +0.20 SD, a 25% chance of being negative, and a 25% chance of being larger than +0.20 SD.

2.6 Conclusion

Index insurance programs have rapidly spread as an alternative to deficient traditional agricultural insurances schemes in developing countries. Given its growing interest by policymakers and researchers, several field experiments have been implemented to document the effectiveness of such programs. In this paper, we aggregate evidence from six randomized controlled trials in a Bayesian hierarchical model to assess the average impact of index insurance on production decisions and investigate the sources of heterogeneity in treatment effects. We find that index insurance has the potential to foster the productive investments of farmers but that these effects are much more uncertain than suggested by the pooling model, with high heterogeneity in treatment effects across studies. The results also rise the concern of low external validity, with only 42% of the observed variation in treatment effects coming from sampling variation. The substantial heterogeneity detected in the by-study treatment effects generates high uncertainty for the predicted effect τ_{K+1} of the programs in a new context. If policymakers were to index insurance programs in comparable environment, the chances of obtaining null or negative results would be non-negligible.

The analysis of individual covariates partially explains the large heterogeneity in treatment effects observed across studies. The evidence shows that worse-off households and the one with lower predicted outcomes experience larger effects from index insurance access. However, the study of additional household covariates does not disclose important sources of heterogeneity in treatment effect. Although lower market prices for index insurance are associated with higher take-ups, they do not translate into higher treatment effects on agricultural decisions. These inconclusive results suggest that other covariates than the one studied in this paper may drive up the heterogeneity in treatment effects on agricultural decisions. In particular, further work is necessary to assess the causal impact of changing features at the study level such as the characteristics of index insurance products.

[16]Findings are robust to using automatic priors (Figure B4). Estimates of τ_{k+1} along the different covariates are also very uncertain (Figure B5

The methodology developed in this paper also illustrates the usefulness of pre-registered report as a tool to collect data when they are not publicly available. In the few examples of meta-studies pre-registration such as Meager (2016), data was publicly available before the registration of pre-analysis plan and authors could not prove that no analysis was run before the registration of the project. In our case, pre-registration is prior to any access to the data and ensures that no searching across outcomes and specifications has been performed earlier on the data. In this context, pre-registration contributes to the literature on research transparency and open science. As such, we see it as a powerful tool to collect data from past experiments implemented at a time when transparency was not so common and generate useful evidence for future research.

Figures and tables

Figure 2.1: The average effect of index insurance on production decisions (τ)

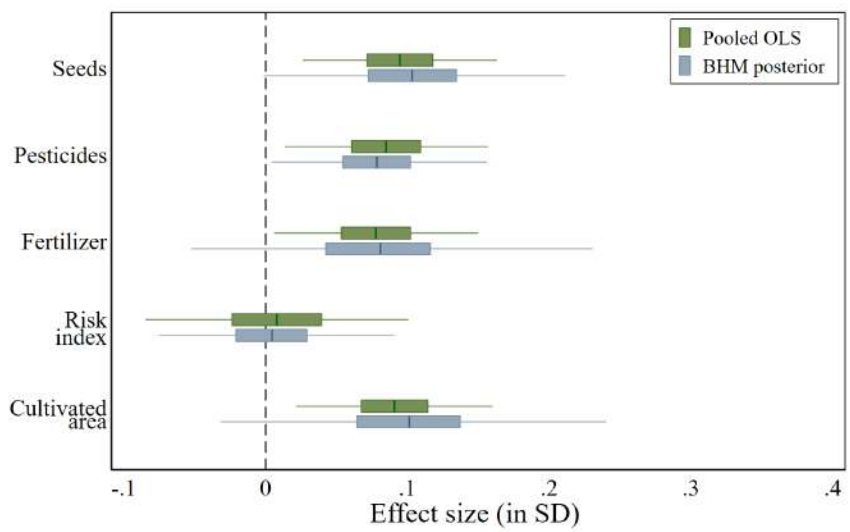

Figure 2.2: The heterogeneity of study-specific treatment effects (τ_k)

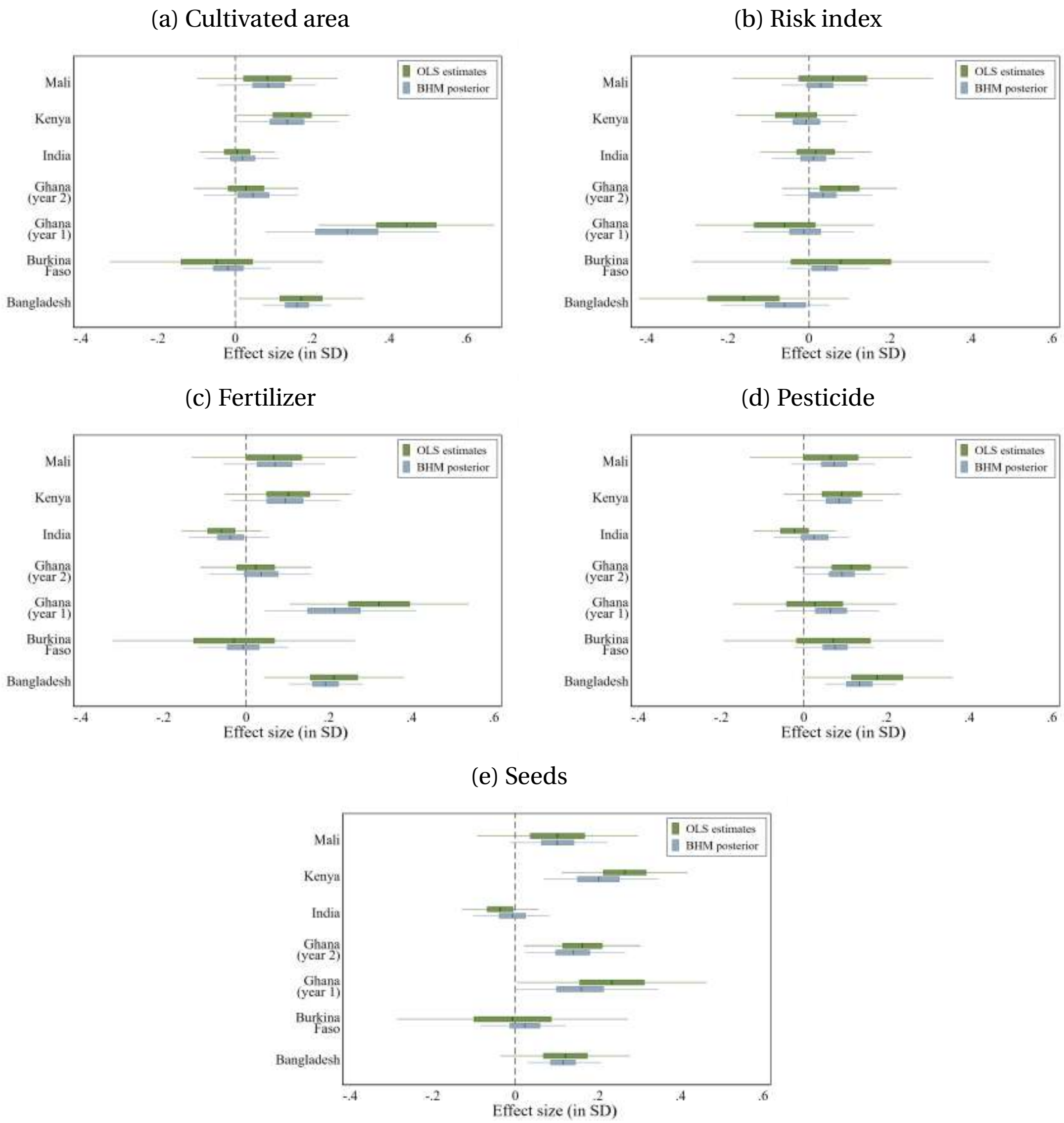

Figure 2.3: The heterogeneity of average treatment effects by key covariates

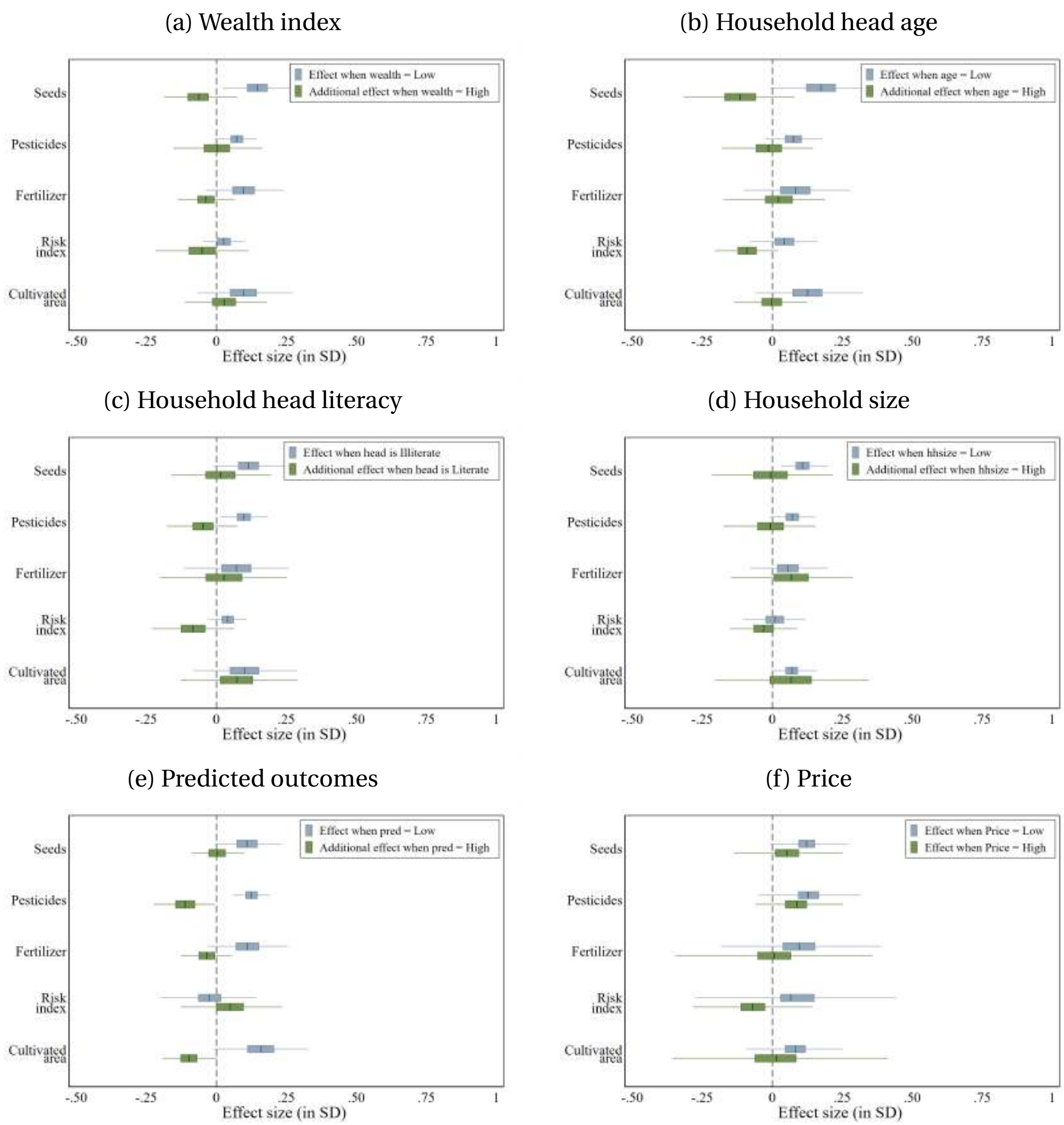

Figure 2.4: The predicted effect of index insurance in the next study (τ_{k+1})

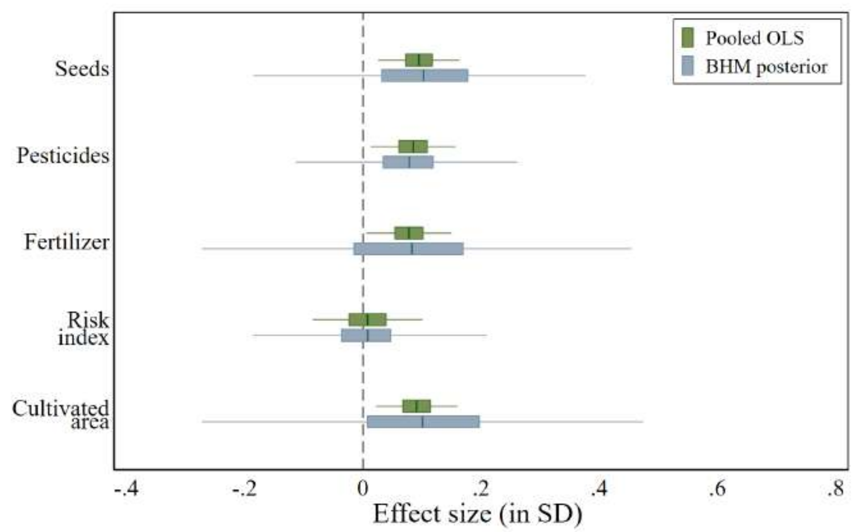

Table 2.1: Studies description

	Bangladesh	Burkina Faso	Ghana		India	Kenya	Mali
			Year 1	Year 2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Citation	Hill et al. (2019)	Stoeffler et al. (2021)	Karlan et al. (2014)	Ibid.	Cole et al. (2017)	Bulte et al. (2019)	Elabed and Carter (2014)
Published[a]	Yes	Yes	Yes	Ibid.	Yes	Yes	No
Data publicly available[a]	No[b]	No	No	Ibid.	Yes	No	No
Start year	2013	2013	2009	2010	2009	2016	2011
Experimental design	Price experiment[c]	Price experiment	Free provision	Price experiment	Free provision	Free provision[d]	Price experiment
Randomization level	Cluster	Cluster	Household	Cluster, household	Household	Household	Cluster
Additional treatment	None	None	Cash grants	Ibid.	Fertilizer coupons	None	None
Eligibility criteria	Membership to GUK[e]	Membership to a farmer group operating with Sofitex[f]	Maize cultivation, less than 15 acres	Ibid.	Land ownership	Membership to a farmer group	Membership to a cotton cooperative
Sampling frame	Villages of the Bogra region	Farmer groups of the Houndé region	Villages in Northern Ghana included in the GLSS5+ survey	Expansion to villages within 30 kilometers of rain gauges	Villages in two districts in Andhra Pradesh, Mahbubnagar and Anantapur	Farmer groups of the Meru region	Cooperatives of the Bougouni region
Baseline survey	Yes	Yes	Yes	Ibid.	Yes	Yes	No
Sample size	2,300	1,015	385[g]	1406[g]	1,479	780	981
Number of clusters	120	80	60	72	45	40	87

[a] As of June 2021.
[b] The published article contains an online appendix with supplementary data. However, the data set only includes the variables analyzed in the original study.
[c] Some of the subsidies took the form of rebates.
[d] Free provision was conditional on purchasing improved seeds.
[e] GUK: Gram Unnayan Karma – local NGO providing a range of services to households in Bogra region, including microfinance, non-formal primary education, primary healthcare, and women's empowerment activities.
[f] Sofitex: Cotton purchasing company.
[g] In year 1, we exclude households receiving only cash grants (N=117). In year 2, it is not clear how many households received only cash grants, but we will also exclude them once we have the data.

Table 2.2: Design of the insurance products

	Bangladesh	Burkina Faso	Ghana		India	Kenya	Mali
			Year 1	Year 2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Type of insurance	Hybrid	Area-yield	Rainfall	Ibid.	Rainfall	Rainfall[a]	Area-yield
Targeted crop	Not crop-specific[b]	Cotton	Maize	Ibid.	Not crop-specific	Four crops	Cotton
Sale price (in PPP USD)[c]	0.3 to 3.3 USD	12.6 to 50.5 USD	Free	1.1 to 15.3 USD	Free	Free (conditional on purchasing improved seeds)	15.8 to 31.6 USD
Actuarially fair price (in PPP USD)[c,d]	3.6 USD	28.9 USD	38.8 USD	7.9 to 10.3 USD	18.0 USD	5.2 to 13.8 USD	31.6 USD
Purchase decision level	Individual	Cluster	Individual	Ibid.	Individual	Individual	Cluster
Unit	Stand-alone policy[b]	1 ha	0.4 ha	Ibid.	Stand-alone policy	0.4 ha	1 ha
Timing of payment	Up-front	After harvest	NA	Up-front	NA	Up-front	After harvest
Take-up[e]	87%	45%	100%	63%	100%	59%	29%
Payoff triggers	Dry spell duration, low average of area yields	Low average of farmer group yields	Number of monthly dry/wet days	Ibid.	Cumulative rainfall	Rainfall excess/deficit	Low average of cooperative yields
Source of data	Weather station, crop-cutting exercise	Purchasing company	Weather station	Ibid.	Weather station	Weather station	Purchasing company
Insurer	NGO	NGO	NGO	Ibid.	Insurance company	Insurance company	Insurance company

[a] The insurance product also includes an indemnity component covering against other risks such as hail, frost, fire, windstorm, and uncontrollable pests and diseases. Indemnities are released after crop stand checks conducted by field inspectors.
[b] While not explicitly tied to a particular crop, each policy was meant to cover revenue from 0.1 acres (0.04 ha) of land cultivated under transplanted aman rice. Households could purchase multiple units of insurance based on the amount of land they cultivate during the monsoon season. According to Hill et al. (2019), this should reduce incentives to view the insurance as a gamble.
[c] Indexed to 2015 dollars. *Source:* World Bank.
[d] In some studies, the actuarially fair price varies depending on the community (Karlan et al., 2014) or crop (Bulte et al., 2019). For example, in Bulte et al. (2019), the price per unit insured is 5.2 USD for sunflower, 10.9 USD for soya bean, 11.1 USD for sorghum, and 13.8 USD for maize.
[e] Take-up is defined as the share of treated households that subscribe to at least one unit of insurance.

Table 2.3: Descriptive statistics

	(1) Bangladesh	(2) Burkina Faso	(3) Ghana Year 1	(4) Ghana Year 2	(5) India	(6) Kenya	(7) Mali
Covariates and predictors[a]							
Household size[b]	4.330	10.417	7.039	6.398	5.151	5.655	19.135
	(1.388)	(6.245)	(3.531)	(3.897)	(2.050)	(1.981)	(13.738)
Head is male	0.961	0.995	0.948	0.709	0.913	0.913	0.999
	(0.194)	(0.070)	(0.222)	(0.454)	(0.282)	(0.282)	(0.032)
Head age	42.723	43.800	44.361	32.097	49.596	46.205	55.387
	(11.767)	(12.928)	(17.306)	(23.341)	(12.404)	(13.916)	(14.950)
Head education (in years)	3.506	1.175	.	.	3.748	6.288	0.984
	(3.941)	(2.465)	.	.	(4.759)	(3.700)	(3.709)
Head literacy[c]	0.490	0.329	0.242	0.256	0.430	0.587	0.415
	(0.500)	(0.470)	(0.429)	(0.437)	(0.495)	(0.493)	(0.493)
Has a bank account	0.293	.	0.078	0.073	0.283	0.262	.
	(0.455)	.	(0.268)	(0.259)	(0.450)	(0.440)	.
Owns land	0.617	.	.	.	1.000	1.000	0.892
	(0.486)	.	.	.	(0.000)	(0.000)	(0.311)
Land owned (in acres)	0.362	.	.	.	5.368	3.183	13.342
	(0.642)	.	.	.	(5.471)	(2.633)	(12.663)
Livestock[d]	0.852	6.391	1.982	1.978	1.542	3.622	1.8e+06
	(0.810)	(9.304)	(3.850)	(5.473)	(2.641)	(3.733)	(4.1e+06)
Weather shock	0.155	.	0.506	0.577	.	.	0.784
	(0.362)	.	(0.501)	(0.494)	.	.	(0.412)
Cultivated area (in acres)[e]	0.707	20.703	9.123	9.140	3.996	2.880	16.384
	(0.592)	(15.614)	(6.244)	(9.806)	(3.592)	(3.114)	(10.159)
Used fertilizers	0.967	0.962	0.691	0.684	0.931	0.851	1.000
	(0.180)	(0.190)	(0.463)	(0.465)	(0.253)	(0.356)	(0.000)
Used pesticides	0.760	0.992	0.395	0.470	0.637	0.841	0.994
	(0.427)	(0.089)	(0.489)	(0.499)	(0.481)	(0.366)	(0.078)
Purchased seeds	0.585	.	0.496	0.447	0.974	0.494	.
	(0.493)	.	(0.501)	(0.497)	(0.158)	(0.500)	.
N	1974	1010	385	1406	1479	780	971

[a] We report the descriptive statistics of covariates and predictors of interest from the raw data provided by the authors.
[b] In Cole et al. (2017), household members below 6 years old are not registered.
[c] In Elabed and Carter (2014) and Bulte et al. (2019), because there is no question on literacy, we proxy it using household head's years of schooling and divide the sample in two groups (above or below average years of schooling).
[d] This variable captures the total population livestock in tropical units, with the exception of Elabed and Carter (2014) in which it represents the value of livestock owned by the household.
[e] We harmonize the unit of cultivated areas across studies by converting all values into acres (1 hectare = 2.4711 acres).

Table 2.4: Pooling factors from the Bayesian hierarchical model

	(1) Fertilizer	(2) Cultivated area	(3) Seeds	(4) Pesticides	(5) Crop risk index
Pooling factors[a]					
Conventional pooling factor λ_1 [b]	0.25	0.25	0.34	0.56	0.60
Generalized pooling factor λ [d]	0.27	0.27	0.37	0.58	0.61

[a] Pooling factors are averaged across studies and belong to the interval [0,1], with 0 indicating no pooling and 1 indicating full pooling. The computations are detailed in appendix B.
[b] The conventional pooling factor λ_1 follows the definition from Box and Tiao (1973).
[d] The generalized pooling factor λ follows the definition from Gelman and Pardoe (2006).

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Chapter 3

The Great Green Wall, a bulwark against children's food insecurity? Evidence from Nigeria

This chapter is joint work with Antoine Leblois (INRAE, CEE-M)and is currently under the status 'Revise and Resubmit' in *American Journal of Agricultural Economics*.

3.1 Introduction

In the 1970s and 1980s, severe droughts stroke Sub-Saharan Africa with harmful consequences on local populations. These tragic events motivated the adoption of The United Nations Convention to Combat Desertification (UNCCD) in 1994 with the dual objective of evaluating the desertification process and providing sustainable solutions against it.[1] This challenge was all the more important and urgent as almost 80% of the Sub-Saharan economy was, at the time, based on subsistence farming. Besides reducing agricultural productivity, land degradation damages livelihoods through food insecurity, water shortage, poverty, health problems and conflicts (Holden and

[1]The UNCCD defines desertification as "land degradation in arid, semi-arid and dry sub-humid areas resulting from various factors, including climate variation and human activities".

Shiferaw, 2004; Couttenier and Soubeyran, 2014; Olagunju, 2015). Following the warming assessment of desertification and its consequences on human well-being, eleven African countries committed to the creation of the Great Green Wall (GGW) in 2007.[2] They agreed to join forces to reforest the region through a 7000 km greenbelt across the continent. Initially designed as a continuous wall of vegetation, the project has evolved to become a mosaic of interventions to restore ecosystems and address the needs of local populations (Goffner et al., 2019). Whether such an ambitious environmental restoration project improves livelihoods of the surrounding households is still an under-explored research question.[3] This paper bridges this evidence gap by assessing the impacts of the program on children's health in Nigeria.

The motivation for the GGW program implementation echoes the growing body of evidence showing that trees-based ecosystem services are correlated to human well-being through diet quality, nutrition or health. Tree land cover helps improving household livelihoods through its capacity to foster agricultural yields and to provide households with products that address basic needs in terms of food, fiber, energy and shelter (Angelsen et al., 2014; Ickowitz et al., 2014). Many case studies bring evidence on the benefit of forests when a shock occurs, such as a crop failure, to complement the income or meet with subsistence needs (Pattanayak and Sills, 2001; McSweeney, 2005; Fisher et al., 2010; Baland et al., 2018). Although trees planted as part of the GGW are unlikely to have reached the minimum height to be considered as forests already, high resolution data of some GGW projects in Nigeria show an important change in trees land cover and raises expectations of preliminary positive effects on welfare outcomes.[4]

Although the literature on trees benefits is important, the focus on their potential positive impacts on children outcomes have been barely analyzed. Yet, early life conditions are known to be very important for individual development (Behrman and Rosenzweig, 2004; Black et al., 2007; Currie and Vogl, 2012). Malnutrition in early stages of life has long-term consequences on human capital attainments such as cognitive scores or health, educational and socio-economic achievements as adults (Glewwe et al., 2001). For instance, Hoddinott et al. (2013) show that individuals who enjoyed a correct growth in the first 3 years of life complete more schooling, score higher tests of cognitive skills in adulthood, have better outcomes in the marriage market, and are more likely to be employed in higher-paying jobs. Similarly, a strong correlation between drought conditions in early childhood and future health and socioeconomic outcomes has been shown for many regions: Hyland and Russ (2019) show that women from Sub-Saharan Africa who experienced water deficits as children are less wealthy as adults, Maccini and Yang (2009) reach similar conclusions

[2]The eleven countries include Burkina Faso, Chad, Djibouti, Ethiopia, Eritrea, Mali, Mauritania, Niger, Nigeria, Senegal and Sudan.

[3]In November 2020, an editorial in Nature journal urged researchers to work on the evaluation of the GGW project and to guide policy-makers towards the achievement of GGW key goals: https://www.nature.com/articles/d41586-020-03080-z

[4]Forests are defined as land cover with trees taller than 5m in height.

for Indonesian women. Therefore, the context in which the child begins her life deserves special attention. Given that children in Northern Nigeria grow up in harsh environment with potential long-term negative impacts of droughts on their individual development, assessing the ability of GGW program to enhance the health during early childhood is a crucial task. This assessment is all the more important that the ongoing process of forest loss in Nigeria has been shown to be associated with worsening children's health conditions (Berazneva and Byker, 2017).

This article contributes to the existing literature on environmental restoration and children's welfare in a number of aspects. To begin with, it is the first to document the local impact of the Great Green Wall program on children's health outcomes. Although Duboz et al. (2019) displayed some correlations between the implementation of GGW in Senegal and welfare and health outcomes, there is surprisingly no causal impact assessment of its consequences on local communities' welfare. Secondly, the distinct analysis conducted on each type of project launched by GGW program allows to determine the specific greening activity that benefits the most to children. Third, we investigate the underlying channels to better capture the source of health improvement for children. Nutrition level is known as the most important factor affecting linear height growth and explains most of the differences in stature among humans (Grasgruber et al., 2014; Perkins et al., 2016). Thus, we build on the dietary diversity score to assess changes in food security of treated and control groups in order to identify potential drivers of children health improvement.

To rigorously assess the impacts of environmental restoration on health and food security, we exploit geographical heterogeneity of children in exposure to GGW projects and conduct a difference-in-difference analysis. The Nigerian Demographic Health Survey (DHS) and the information on the location of GGW projects, both geocoded, are combined to assign a treatment status to the community where the children live. Three distance cutoffs between the community and the project are used to define the treatment status, with a baseline specification at 15 km. The identification relies on the quasi-experimental variation in environmental restoration programs implemented between late 2013 and 2016 in the northern regions of Nigeria. We draw from 2013 and 2018 DHS and their rich information about health status, in particular anthropometric measures for children. However, the main identification suffers from the lack of credible counterfactual given that the program was targeted and not randomly allocated to households. To overcome this challenge, we augment the estimations with propensity score reweighting and parallel trends checks for the period preceding the GGW projects. This empirical methodology stays constant when we investigate the changes in children nutrition proxied by their dietary diversity score.

The findings are twofold. First, the children living next to areas where environmental restoration programs have been implemented appear to be in better health than those who live further from the projects. In particular, this result survives all the specifications when the local project is a community orchard, with an important increase in heigh-to-age standard deviation. The results are robust to several alternative specifications. At 10 km, 15 km and 20 km, children benefit from the orchards. The evidence about the impacts of shelterbelt activities is mixed and heavily depends on the specification involved and the threshold of treatment defined for the analysis. Second, the dietary diversity score of local children significantly and positively increases, bringing evidence that health improvement mainly occurs through better food access in the case of orchard treatment. In addition to the mixed results of shelterbelts impacts on HAZ score of local children, we find no evidence of better food access for children living in nearby communities.

The remainder of the paper proceeds as follows. Section 3.2 introduces the context of the new environmental restoration program implemented in Nigeria as well as the data used in the analysis. Section 3.3 describes the identification strategy and section 3.4 displays the results. Section 3.5 concludes.

3.2 Context and Data

3.2.1 The Great Green Wall in Nigeria

The program

The Great Green Wall is a Pan-African initiative spearheaded by the African Union and funded by the World Bank, the European Union and the United Nations. The idea was formally approved in 2007 to slow down the expansion of the Sahara by planting a barrier of trees spreading 7000 kilometers from Senegal to Djibouti.

With the rising concerns about climate change in the Sahel region, the greenbelt intends to fill a new role: increasing the vegetation cover to eventually mitigate food insecurity, land conflicts and migration for millions of farmers living in the region. On its official website, the project promises "to bring life back to Africa's degraded landscapes at an unprecedented scale, providing food security, jobs and a reason to stay for the millions who live along its path".[5] To this end, more than eight billion dollars have been mobilized and pledged for its support.[6]

The project has been progressing at different scales among the eleven countries committed to give birth to the GGW.[7] In Nigeria, the implementation of the project has been starting in 2013 with about 6,000,000 plants produced mainly for shelterbelts and orchards managed at the community level. The program covers eleven northern states of the country. The National Council on the Great Green Wall (NCGGW) is the governing body deciding and monitoring the implementation of the program

[5] https://www.greatgreenwall.org/about-great-green-wall

[6] https://www.unccd.int/actions/great-green-wall-initiative

[7] The focus on the Nigerian case stems from the lack of national data on GGW implementation for other countries involved in the project.

at the national level. At the community level, the head of the community decides how to redistribute revenues or products from the activities across households.[8]

All these activities have generated about 20,000 jobs.[6] The UNCCD claims that the GGW initiative trained and engaged 498 youths as forest guards, several thousands in planting and other related activities and more than a thousand in drilling boreholes. According to Gadzama (2017), more than 100,000 people in the rural areas will be employed during the whole period of projects implementation, beside the 1000 forest guards and 450 extension workers that will be required.

The implementation of the GGW project takes different forms in the country. Shelterbelts are rows of trees to protect soil from erosion and improve the quality of farmlands. Between 2013 and 2016, 642 kilometers of such shelterbelts grew along the northern part of the country. About 300 hectares of community orchard have also been established to provide edible products such as mangoes, guavas, cashews, or oranges among others. More than a hundred solar and wind-powered boreholes have been constructed to support the maintenance of shelterbelts and orchards, and are supposed to provide water to over 40,000 people and 150,000 livestock (PAG, 2018).

Given that features and interests associated with each type of project differ (as discussed in 3.2.1, looking at ecosystemic services), we decide to separately assess the impacts of orchards and shelterbelts on households' livelihood.

The data

The first task to answer our research question is to locate the environmental restoration projects implemented through the GGW program. To this end, the NCGGW provided data on the localisation and year of implementation of about a hundred of orchards and boreholes and of more than two hundreds of shelterbelts (Table 3.1). Geolocalization of the activities, along with the type of the project, were made available for our research project. Figure 3.1 provides an overview of the different types of projects implemented as part of the program between 2013 and 2016. Most of the boreholes are placed in the very vicinity of orchards or shelterbelts in order to increase the lifespan of both types of projects. Figures C1, C2 and C3 illustrate the scope of such projects, by showing remote sensing images of different types of projects before and after their implementation.[9]

[8]The land where the projects take place mainly belong to community members' institutions. The land that belongs to the community members are voluntarily donated for the benefit that comes with the project because after an agreed period of time, the community members will take over the sustainability of the land and enjoy whatever proceeds gotten from the project.

[9]A systematic monitoring and checking of the GPS data is very complex since many projects are not observed at the right date. The seasonality in vegetation makes it hard to distinguish projects since an image is not available every year.

Tree planting programs often face great challenges (Holl and Brancalion, 2020). Previous land restoration programs in Nigeria were actually suspected of weak integration and notable gaps in civil society participation, absence of use of indigenous knowledge, limited community and farmers implication, and limited maintenance (Jalam et al., 2020; Medugu et al., 2010).

These limitations resulted in low shelterbelts survival rates.[10] To ensure a sustainable implementation of the current program, policymakers try to learn from past errors in national land restoration initiatives, notably by involving community members in the land use policy and redistribution of projects' revenues and by adopting bottom-up approaches.

Ecosystemic services and other potential impacts

Environmental restoration programs, and more particularly land restoration, is known to enhance various ecosystemic services (Benayas et al., 2009). Ecosystemic services from trees in Sudano-Sahelian West Africa includes from pest control, soil nutrient concentration, erosion control, carbon storage, water flows regulation, shade provision, and regulation of micro climates (Sinare and Gordon, 2015; Davies, 2017). Those services impact local communities mainly by fostering agricultural yields, by reducing the probability and impacts of floods or heatwaves, and by contributing to groundwater recharge. The most important impacts of tree planting, such as shelterbelts, on agricultural yields in arid environments probably comes from the limitation of soil erosion, the protection against windstorm and the run-off and evapotranspiration regulation (Adesina and Gadiga, 2014). Pest control plays also a key role in Nigeria: millet growing under acacia trees was not found infected by the millet pest striga, in contrast to surrounding areas (Gworgwor, 2007).

Such improvements in soil condition consequently result in vegetation development in areas where shelterbelts are established (Adesina and Gadiga, 2014). Limiting soil erosion has indeed been proved to positively impact crop growth yields in the case of millet in Nigeria (Abubakar, 2014) and more generally in the Sahel (Michels et al., 1998). Tree roots also help maintaining soil health by improving soil structure, increasing diversity in the soil and supporting soil biology by keeping it covered but also by providing food and shelter for living organisms. The shelterbelts, according to the people's perceptions, have significantly reduced the incidence of destructive windstorm on crops and improved the living environment of humans (Abubakar, 2014).

Planting trees in arid environments also provides water availability and reduce floods through water flow regulation: it limits rainfall run-off and favorises groudwater recharge by fostering water infiltration. By increasing water holding capac-

[10] Igugu and Osemeobo (1990) reported that between 1963 and 1989 over 236,500 hectares of shelterbelts were established in the States threatened by desertification in Nigeria.

ity, tree roots regulate the water cycle and limits downstream flooding by increasing evapotranspiration (Zhang et al., 2017; Zhang and Wei, 2021). Globally up to 40% of rainfall originates as upwind land evaporation (Keys et al., 2016). McCarthy et al. (2021) show that green belts are effective to reduce flood risk for maize production in Malawi and Ilstedt et al. (2016) that tree densities influence groundwater recharge in Burkina Faso.

In addition to ecosystemic services, tree planting may also improve income from medicinal, social, cultural, food additive, energy and material uses (Sinare and Gordon, 2015). Having fruits from trees available during the hungry season may have significant impact on income, food security and diet diversification. Some species are identified to play a major role during certain seasons, or gain importance during drought years. Ickowitz et al. (2014) found a statistically significant positive relationship between tree cover and dietary diversity. Their findings suggest that children in Africa who live in areas with more tree cover have more nutritious diets.

Trees may finally bring shade and food to livestock (fodder), and thus manure in cultivation fields from animals browsing trees. Similarly the importance of woody vegetation to sustain livestock is higher during the dry season (Sinare and Gordon, 2015). It more generally creates habitat and provides shelters, for many species, increasing biodiversity support.

3.2.2 Health of Nigerian Children

In this paper, the main source of socio-economic data is the nationally representative Nigeria Demographic and Health Surveys (DHS). DHS are cross-sectional surveys designed to provide information on households characteristics, health and living conditions at the national. The data are geocoded at the DHS cluster/community level. For confidentiality issues, the DHS program displaces the latitude and longitude of the clusters. In particular, urban locations are displaced 0-2 kilometers while rural locations are displaced 0-5 kilometers with 1% displaced 0-10 kilometers for anonymity purposes. We make use of data available for 2013 and 2018, two years surrounding the implementation of Great Green Wall projects. In order to perform parallel trend tests, DHS are also extracted for the year 2003.[11] We restrict our sample to rural households belonging to the eleven Northern States where GGW projects

[11] Nigerian DHS are available for the year 2008. However, the food security indexes that could be extracted from these data might be greatly distorted by the National Special program for Food Security (NSPFS) implemented in Nigeria right before the 2008 DHS collection. The broad objective of the NSPFS was to contribute to sustainable improvements in national food security through increases in agricultural productivity and food production. Several sites in northern Nigeria were selected to receive field activities from the 2003 cropping season to 2006. More information about implementation and objectives of the program is available here: `www.fao.org/3/a-bd346e.pdf`.

have been implemented.[12]

All surveyed women aged between 15 and 49 years old present at the time of the survey are interviewed. Each of their children who are less than 5 years old are subject to anthropometric measurements. In particular, height was measured in order to establish a height-for-age index and compare it to standards provided by the World Health Organization (WHO). The height-for-age indicator informs on the long-term nutritional status of the child and captures recurrent or chronic illness at an early age. When the height-for-age standard deviation (HAZ) from the WHO 2006 study medians is below minus two, the child is considered as stunted or chronically undernourished. Children whose HAZ score is below minus three standard deviations from the median are considered severely stunted. The DHS Final Report conducted in Nigeria in 2018 reveals that 37% of Nigerian children below 5 years old are stunted. Investigating HAZ score allows us to capture the impacts of environmental reforestation on children health and food security on a long term, independently from recent changes in dietary intakes.

The children are assigned with a treatment status according to the distance of their community to the GGW project, with a threshold established at 15 kilometers for the main specification. Table C1 shows the distribution of children across control and treated areas defined by a 10 km, 15 km and, 20 km buffer around the centroid of the project. Figure 3.2 distinguishes children located close to an orchard or a shelterbelt project and shows their average HAZ score across the three waves of DHS. Even though the 2003 average HAZ score is lower for the children living in the area selected for orchards implementation, both treated and control children experience health improvement following a parallel trend until 2013. During the period of orchards implementation, HAZ scores display downward health trends for control children (from -1.99 to -2.28, i.e. -15 %) and positive change in HAZ score for the treated group (from -2.39 to -2.26, i.e. +1%). If we consider the shelterbelt projects, we see that health conditions has increased in the treated group (from -2.62 to -2.22, i.e. +15%) while it has decreased for the control group (from -2.02 to -2.28, i.e. -13%). Further investigation helps understanding whether this difference in health evolution between treated and control children is driven by the implementation of environmental restoration projects.

3.3 Empirical Framework

The goal of this empirical study is to identify how the Great Green Wall enhances rural livelihoods for the local communities. To this end, we explore variations across time (the project occurence) and space (children's community distance to the projects).

[12] These states are Adamawa, Bauchi, Borno, Gombe, Jigawa, Kano, Katsina, Kebi, Sokoto, Yobe and Zamfara.

This actually refers to a difference-in-difference methodology. To do so, it is crucial to determine a treated and a control group at best.

Most of the geospatial difference-in-difference using distance cutoffs to assess health impacts comes from mining and industrial impact evaluations. To our knowledge, there are no papers relying on similar methodologies to assess the impact of environmental restoration programs on health outcomes for surrounding communities. Therefore, we learnt from the studies of mining in economics and test several thresholds from 10 to 20 km , with a baseline distance at 15 km from the GGW project. Apart from von der Goltz and Barnwal (2019) who work on tight distances at the expense of unbalanced panel, most of the authors studying the health impact of industrial areas define and assign the treatment status using larger bandwidths. Benshaul-Tolonen (2019) works with a minimum baseline distance fixed at 10 km whereas Wilson (2012), Kotsadam and Tolonen (2016) and Aragon and Rud (2016) use a baseline cutoff of 20 km and run sensitivity analysis to other thresholds.

With precise data, we might define closeness even more restrictively. However, in the context of available data, we think that the 15 km distance cut-off is reasonable for two reasons: (1) the practice of jittering DHS cluster geolocations (displaced up to 5 km, and up to 10 km for 1% of the sample) risks introducing excessive noise if the cut-off is tight; and (2) the sample size of treated households increases rapidly with distance (see Table C1), which increases the power of the results, all else equal.

The 15 km distance cutoff is eventually motivated by empirical evidence on commuting distances in rural Africa, showing that areas of 10 or 15 km are likely integrated markets (Schafer, 2000; Amoh-Gyimah and Nimako Aidoo, 2013; Kung et al., 2014). At this distance, we can reasonably expect households to take part in the projects as direct employees as well as potential buyers of food products from newly created orchards.

Once we have assigned a treatment status to the community, we rely on difference-in-difference to assess the impact of the treatment on children's height-to-age standard deviation. The following equation illustrates the canonical set up with two units and two time periods, with one of the units being treated in the second period:

$$\begin{aligned} Y_{ijmys} = \beta_1 POST_j.TREAT_j + \beta_2 POST_j + \beta_3 TREAT_j + \\ \beta_4 X_{ijmys} + \alpha_m + \alpha_y + \alpha_{my} + \alpha_s + \epsilon_{ijmys}. \end{aligned} \tag{3.1}$$

with Y_{ijmys} being the anthropometric measurement for child i born in month m in year t and living in community j from state s. $POST_j$ and $TREAT_j$ are dummy variables equal to one if the child's community is in the post-treatment period and belongs to the treatment area respectively. β_1 is the coefficient of interest, also called the treatment effect; it gives the estimated impact of the change in greening areas on the health of children who live next to a GGW site. We control for the unobservable conditions during the very beginning of life by including month of birth m, year of birth y, and month by year of birth my fixed effects. One specification includes geographic fixed effects at the state level s to control for state-linear time trend. X_{ijmys} include covariates that may influence the initial estimates on health outcomes such as sex and age of the head of the household, the size of the household, the birth order, the distance to the nearest water source, the education/marital/religion/body mass index of the mother and the number of droughts registered on the period 1980-2000. To avoid as much as possible "fake controls" (households considered as control whereas they are treated), we exclude from the analysis any children located between the distance cutoff and twice its distance.[13] $POST_j$ and X_{ijmys} are also interacted for sensitivity checks. In all models, we cluster standard errors at the DHS cluster level, which corresponds to community j.

Propensity Score Reweighting In this quasi-natural experiment, the treatment assignment is not randomly operated. The table 3.2 brings evidence that there are persistent differences across treated and control households at baseline. Among the multiple techniques that have been developed to help researchers capturing the impact of a program on individuals or households with different characteristics at baseline, we decide to employ the Inverse Probability Weighting (IPW) method. Its ability to recover unbiased estimates of average treatment effects in observational studies has made this method very attractive for causal inference (Hirano et al., 2003; Austin and Stuart, 2015). The approach consists in estimating the probability of treatment assignment conditional on observed covariates, also called the propensity score, and using it to reweight each observation from the data. To be more specific, the estimated probability of being treated by a project for observation i, denoted p_i, is computed based on the set of covariates X and the geographic fixed effects.[14] Using this probability, we derive weights $\frac{1}{1-p_i}$ and $\frac{1}{p_i}$ assigned to non-treated and treated observations respectively.[15]

Parallel trend checks The parallel trend estimations aim at checking whether treated and control children had similar health trends before the occurrence period. 2003 and 2013 DHS are two pre-treatment waves available to check for parallel trends. It allows to build a credible counterfactual for the control group and tests if any difference occurs during the pre-treatment period. We do so by replicating the baseline estimations on the pre-treatment period 2003-2013, with the difference that children from 2013 DHS wave are considered to belong to the post-treatment period ($POST_j = 1$).

[13]In the case of 15 km treatment for instance, the children located between 15 and 30 km are dropped from the regressions.

[14]In our case, this estimation relies on a logit estimator.

[15]The propensity score reweighting is separately executed for Orchard and Shelterbelt treatments.

Impact heterogeneity: duration of exposure to treatment We then look at discrepancies in impacts according to the duration of exposure to treatment, that varies between 2 and 5.4 years, depending on the year of the project implementation and the birth date of surveyed children. We provide visuals of the heterogeneity of the impacts, depending on the treatment duration (section 3.4.2).

In Figures C5 and C4 we show the same visuals depending on the age of children at treatment. These figures allow to visually assess how much treatment may depend on the duration of exposure to treatment and children's age at treatment, without providing a really robustly significant evidence.

Channels Investigation Eventually, we use the same difference-in-difference methodology and run the equation 3.1 to investigate the change in dietary diversity for children surveyed in the DHS. The results are introduced in section 3.4.3. To do this, we compute a dietary diversity score at the child level. This dietary diversity score is increasingly accepted as an essential component of healthy diets and associated with nutrient intake and thus recognized as a good proxy for food security (Ruel, 2002). We restrict the analysis to children between the ages of 12 and 60 months because children are heavily dependent on breast milk during their first year and thus have limited diets. The dietary diversity score is the number of food groups consumed by a child during the last twenty-four hours. The score ranges from 0 to 10, 10 being the maximum number of nutritional food groups including cereals, roots and tubers, vegetables, fruits eggs, meat, fish and seafood, milk and dairy products, pulses and nuts, and beverages.

Robustness checks Several robustness checks are run to complement the main analysis and discuss the persistence of the results with more details. First, we alternatively control for geographic linear-time trends by using fixed effects at the annual cumulative rainfall averages level in C4.[16] To restrain the sample to areas with comparable environments, the tables C3 exclude from the analysis the children located more than 100 km away from the closest GGW project. In appendix C6, we finally compare the magnitude of the coefficient estimates when the project is jointly created with a borehole.

We explore the possibility that our results could be unspecific to GGW activities, but rather due to other factors that would correlate with systematically better health around places where projects settled. For instance, we could suspect that the critical food insecurity situation in the areas targeted by the GGW program could have also attracted new health or development programs. To rule out the hypothesis that HAZ score improvement is driven by local health programs, we run a fake treatment

[16] We built 10 rainfall zones, using average annual cumulative precipitations over the 1980-2015 period. The 10 rainfall zones correspond to the deciles of the distribution of long run average cumulative precipitations in all DHS clusters considered.

on alternative health outcomes such as the incidence of cough, diarrhea, and fever. In the same appendix C8, we also assess the impact of proximity to GGW projects on children's weight-to-height and weight-to-age z-scores to measure for potential short-term impacts on health.

Eventually, the analysis involves a concern about residential sorting, that is the possibility that households with different potential health outcomes may be selectively moving in or out of an area targeted by the GGW program. To control for this issue, we estimate the same specifications only with the sample of children belonging to households who have not moved between 2013 and 2018 (see appendix C2).

3.4 Results

3.4.1 Main results

All the tables from this section are split between the panel with children surveyed for the period of interest (2013-2018) and the children surveyed during the pre-treatment period (2003-2013).

Table 3.3 displays the results of the difference-in-difference estimation of the orchard 15 km buffer treatment on children's height-to-age standard deviations. The results show persistent positive and significant causality between orchard development and children's health across all specifications. The coefficients range from 0.24 to 0.72 according to the specification at stake. Living in a community with at least one orchard at 15 km significantly increases the height-for-age by 0.56 standard deviations in the most conservative specification. In order to interpret the magnitude of the effect, we compare the coefficient estimate to the pre-treatment control mean group and find that children in treated areas benefit from a 28% health improvement proxied by HAZ score relatively to children from control areas.[17] The parallel trend estimates aim at checking whether treated and control children had similar health improvement trends before their exposure to environmental restoration projects. The lower panel in Table 3.3 shows that none of the parallel trend estimates of β_1 are statistically different from zero across all specifications. Living in the areas that would later be exposed to orchard activities did not imply a specific trend in terms of children's health improvement.

Results are robust to the exclusion of children born to recent migrants (C2). Excluding all mothers who arrived after the launch of orchard projects slightly increases the treatment effect. This indicates that the positive impact of orchard activities on health is not driven by children from newly arrived households. The positive im-

[17] The Balance Table 3.2 shows that the mean HAZ score for control children was -1.973 at the time of pre-treatment.

pact of orchards activities on children HAZ score is also robust to the exclusion of children living further than 100 km from an orchard (C3) and to alternative specifications with annual cumulative rainfall averages fixed effects (C4). Eventually, Table C6 shows that the magnitude of the impact is similar when the orchard is coupled with a borehole. Figure 3.5 plots the coefficient estimates for the three thresholds for treatment assignment and shows that the positive impact on health of being close to at least one orchard persists at 20 km.

Table 3.4 displays the results for the DiD estimation for the other main treatment assignment, that is the proximity to shelterbelt projects. The positive and significant results identified in the first specifications do not hold when state fixed-effects are included, showing that the positive relationship between proximity to at least one shelterbelt and the improvement in HAZ score is affected by omitted variable bias due to factors that are constant over states. Robustness checks such as the one including annual cumulative rainfall averages fixed effects instead of state fixed effects (C5) and the one excluding children living more than 100 km far from a project (C3) provides significant estimates of the impact of shelterbelts on HAZ score of the children from communities at 15 km. However, the most restrictive specification of these models show positive coefficient estimates significant at the 10% only. Figure 3.5 shows that positive impact of shelterbelt activities on children's health are expected on short distances, such as 10 km, but fails to benefit to further communities. Put together, the mixed evidence from the different specifications and robustness checks prevents us from concluding on a strong impact of shelterbelt activities on health of children living more than 10 km far from the projects.

Table C7 in appendix introduces the coefficients when the treatment definition includes all type of projects together, such as orchards, shelterbelts or boreholes. Cumulative effects of the three types of projects show significant and greater magnitude than one type of project alone.

Eventually, Table C8 shows that alternative health outcomes such as fever, cough, and diarrhea, are not significantly affected by the proximity to GGW activities. This mitigates the hypothesis that other health or development projects have been implemented in same areas as the Great Green Wall and strengthens the causal impact of the environmental restoration programs on health improvements.

3.4.2 Heterogeneous impacts

Taking advantage of variations in birth date (month) and project year information, we draw the average height-for-age of treated and control groups that is not explained by covariates or fixed effects. Figures 3.3 and 3.4 show these unexplained changes in height-for-age in control and treated clusters depending on treatment duration, respectively for orchards and shelterbelts projects. The duration of treatment is the time between project implementation and survey interviews.

Visuals are plotting the local polynomial smooth of residual of the most robust specification (5) in Tables 3.3 and 3.4 (equation 3.1, with all fixed effects) excluding the two treatment variables, by duration of exposure to treatment. Figures 3.3 and 3.4 thus show the average residuals in height-for-age in control and treated groups, for a treatment distance of 15 km, i.e. that may not be explained by covariates and fixed effects. In these graphs, control groups are different depending on the project considered: a buffer of 15 to 30 km that is considered around each project, excluding children that may be partially treated.

A visual inspection reveals that being close to a project increases the height-for-age after two years and that this impact decreases for shelterbelts while it is stable in time for orchards. The decrease in the impact of shelterbelts after two years may be explained by the above-mentioned anecdotal evidence of a relatively short life span of shelterbelts implemented in the 90's. It was particularly suffering from drought and a lack of maintenance and efforts from neighbouring populations to keep trees alive. The implementation of borehole projects from 2014 onwards, supposed to increase projects life span, may thus have had a limited impact on shelterbelts.

Robustness of these graphs may be questioned for two main reasons: (i) intra-annual treatment duration in month stems from variation in birth dates, since project implementation is observed on an annual basis; and (ii) there are very limited observations between 0 and two years of treatment, heterogeneity should thus be only considered after this 2 years period.

We also provide and discuss similar evidence of heterogeneous impacts depending on the age at treatment in Figures C5 and C4. We show that the effect of orchards and shelterbelts are significant when the treatment occurs in early childhood: before the third year for shelterbelts and before the fourth year for orchards.

3.4.3 Channels

The previous results show to which extent the impact of the project plays a key role for health improvement for children who were living nearby, in particular when community-based orchards are at stake. Following the literature, we consider that nutrition and food intake in early stages of life is a determining factor in health status. Therefore, we rely on additional information from DHS to study if this health improvement is driven by some changes in the dietary diversity for children belonging to the treated communities.

Table 3.5 displays significant changes in the dietary diversity score of children living within a 15 km buffer of at least one orchard. In the most conservative restriction, living close to at least one community-based orchard is associated with a 0.5 increase in the dietary diversity. This corresponds to a 29 % increase in the children dietary diversity score in comparison to the mean of the control group at the pre-treatment period referenced in table 3.2. These results are in line with the robust persistent health improvements for children living nearby orchard projects. The diet of children living in communities near shelterbelts do not appear to be significantly more diverse.

A first interpretation of these results builds on the 20,000 jobs created for GGW implementation in Nigeria and assumes that the more diverse food consumption reflects an additional income earned by local communities. A second assumption relies on the capacity of orchards to provide edible products to the surrounding households, hence participating directly into food security improvement. Unfortunately, DHS data do not allow us to further investigate these transmission channels.[18]

3.5 Conclusion

Western African households are particularly vulnerable to growing soil erosion under arid climate. This harmful process leaves them with fewer alternatives to find sources of edible products and to protect their lands. In 2007, policy makers across the continent committed to an environmental restoration program named the Great Green Wall. This paper presents the first evidence that an environmental restoration program, such as the GGW in Nigeria, improves children's health by providing better food access to the local populations. We match nationally representative socio-demographic surveys to precise location of Nigerian GGW environmental restoration projects to explore the impact of the program on children's height-to-age and dietary diversity score. The heterogeneous exposure to the projects in time and space allows to distinguish treated households from control one and establish a difference-in-differences methodology. Parallel trend estimations and IPW method enrich the empirical framework and control for the identification issues that may occur from the not-random location of the projects.

The results have important implication for program design since they inform about the specific types of GGW activities that benefit the most to local children. First, the estimates show a positive and long-distance impact of orchard activities on children health whereas shelterbelts are associated with strong health improvement of children at a short distance only. More specifically, the children living at less than 15 km from at least one community-based orchard enjoys a 28% increase in height-to-age standard deviation relatively to children from control areas. The orchards seem to have long distance impacts on children health since some positive spillovers are still captured at 20 km. We show evidence that this health improvement mainly occurs through better dietary diversity for the surrounding children.

[18]Some analysis has been run on the impact of GGW projects on labor outcomes but the main caveat is that the recall period for labor activities is 12 months and doesn't capture any employment at the time when the project was created.

As first causal impact evaluation of the Great Green Wall program, we believe that this paper provides useful preliminary evidence on the positive spillovers of land restoration projects. However, the Great Green Wall has been implemented heterogeneously across Sub-Saharan Africa. For instance, Niger decided to distribute grains to the local population whereas Burkina Faso tried to rehabilitate lands through the development of traditional practice in the communities. Therefore, our results are specific to the Nigerian case but does not provide an overall assessment of GGW effectiveness. The vast range of initiatives undertaken to restore lands deserve a cross-country and comparative analysis to better capture the specific greening activities that may benefit the most to the local population. The growing availability of remote sensing data and household surveys with GPS coordinates offer a promising path to investigate this question in other settings.

Figures and tables

Table 3.1: Distribution of projects studied over the 2013-2016 period

	Year of establishment				
	2013	2014	2015	2016	**Total**
Orchard	8	43	45	4	**100**
Shelterbelt	45	57	114	0	**216**
Borehole	10	50	43	1	**104**
Total	**63**	**150**	**203**	**4**	**420**

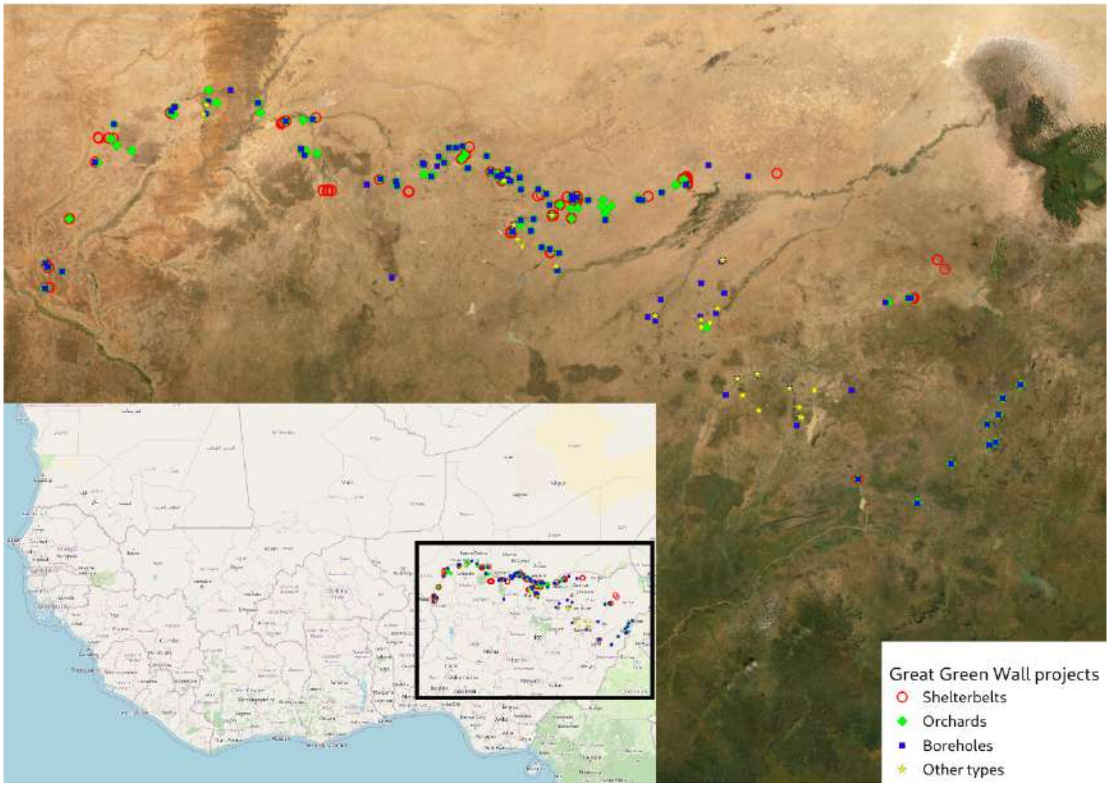

Figure 3.1: Location of Great Green Wall Projects in Nigeria

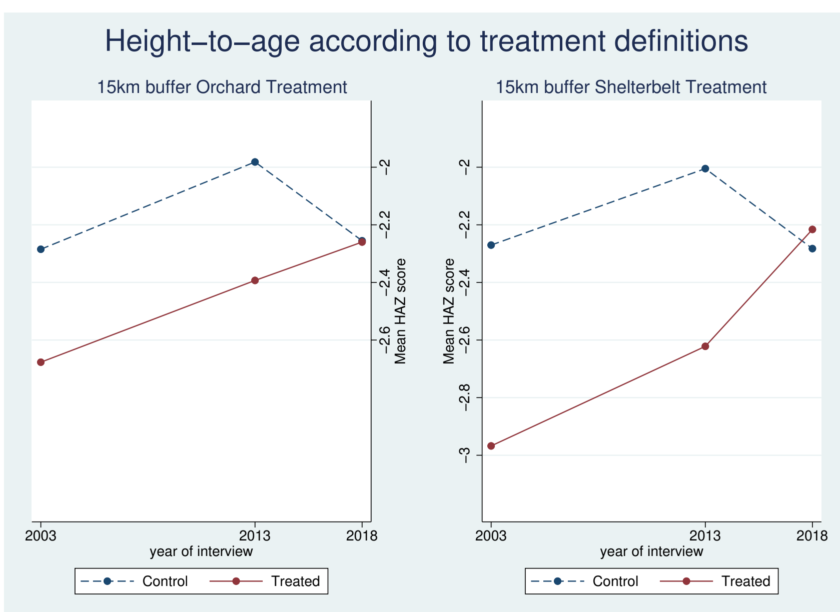

Figure 3.2: The evolution of height-to-age z-score under two treatment definitions

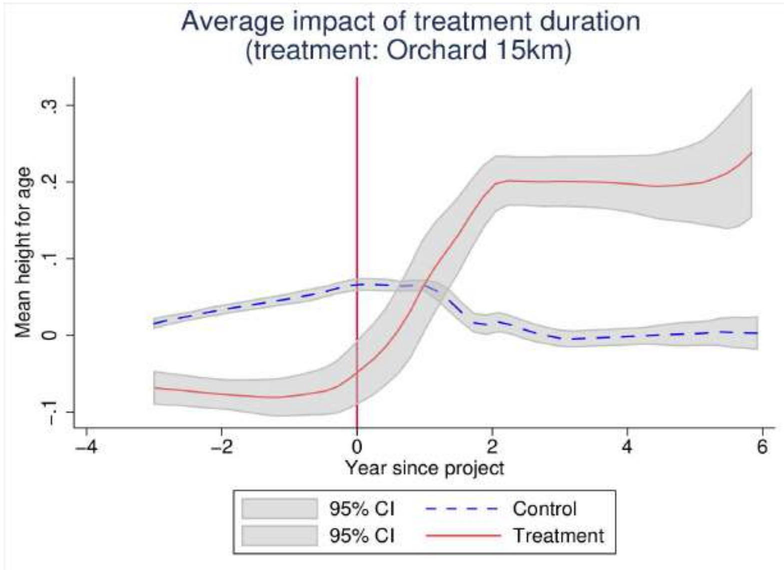

Figure 3.3: Kernel Weighted Local Polynomial Smooth of height-to-age for orchard treatment
Note: The graph depends on the time after before treatment, ranging from 3 years before to 6 years after. The treatment group is drawn within 15 kilometres from the closest orchard (treatment), and the control group at more than 30 kilometres from the closest GGW project.

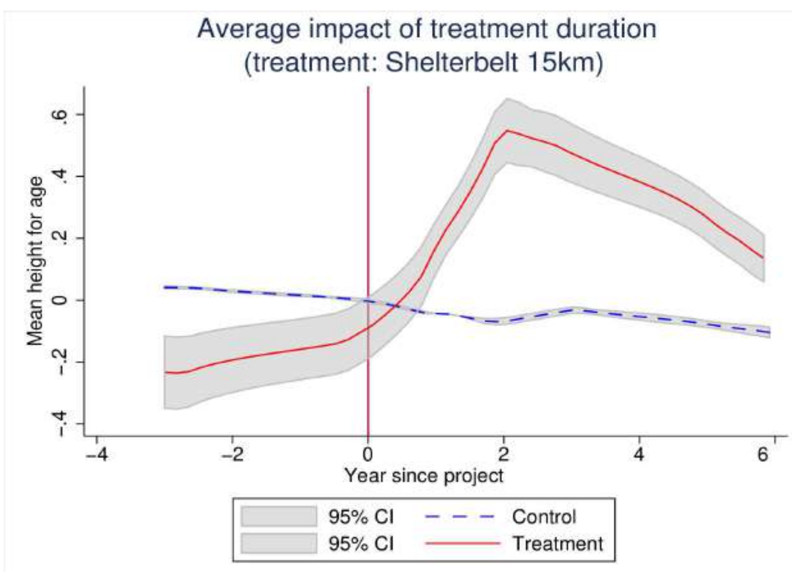

Figure 3.4: Kernel Weighted Local Polynomial Smooth of height-to-age for shelterbelt treatment
Note: The graph depends on the time after before treatment, ranging from 3 years before to 6 years after. The treatment group is drawn within 15 kilometres from the closest hhelterbelt (treatment), and the control group at more than 30 kilometres from the closest GGW project. It also provides 95% confidence intervals.

Table 3.2: Balance Table for Pre-Treatment Year for children in 2013 DHS

Variable	Control group	Treatment group	Difference
height/age standard deviation (new who)	-1.973	-2.337	-0.365***
	(2.063)	(1.974)	(0.065)
Scale of food diversity for the child from 0 to 10	1.704	1.616	-0.088
	(1.914)	(1.778)	(0.061)
Number of household members	7.862	7.540	-0.322***
	(3.668)	(3.482)	(0.097)
Sex of household head	1.041	1.031	-0.010*
	(0.197)	(0.173)	(0.005)
Age of household head	41.202	40.260	-0.941***
	(11.735)	(11.267)	(0.309)
Education in single years	1.297	0.553	-0.744***
	(3.005)	(1.937)	(0.075)
1 if respondent is Christian, 0 if not	0.056	0.003	-0.053***
	(0.230)	(0.053)	(0.006)
1 if respondent is Muslim, 0 if not	0.929	0.991	0.063***
	(0.258)	(0.092)	(0.006)
1 if respondent is currently married, 0 if not	0.974	0.991	0.017***
	(0.159)	(0.092)	(0.004)
Time to get to water source (minutes)	19.338	22.041	2.702***
	(28.120)	(24.261)	(0.730)
Drought Episodes	6.419	4.621	-1.798***
	(2.276)	(1.638)	(0.058)
Body mass index of the mother	2,188.108	2,102.707	-85.401***
	(383.704)	(328.123)	(10.036)
Birth order number	4.513	4.562	0.049
	(2.832)	(2.856)	(0.075)
Observations	7,420	1,751	9,171

Treatment group includes all the rural children who are less than 15 km far from any Great Green Wall Project, including orchards, shelterbelts, and boreholes. *** p<0.01, ** p<0.05, * p<0.1.

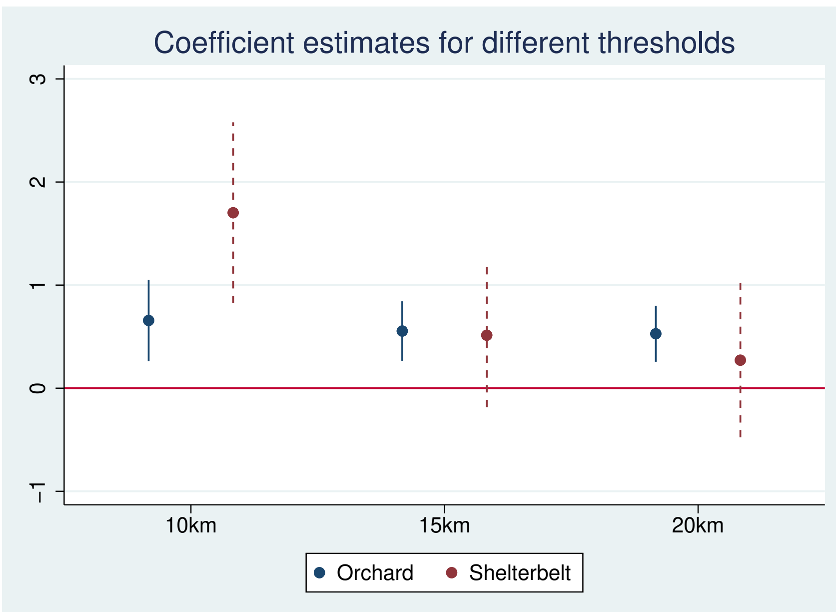

Figure 3.5: Evolution of coefficient estimates of HAZ scores following different treatment thresholds.

Note: The coefficient estimates shown in this figure are the results of the most restrictive specification including covariates, all fixed effects and propensity score reweighting.

Table 3.3: Impacts of orchards on children height-to-age z-score

	Orchard treatment at 15 km				
	(1)	(2)	(3)	(4)	(5)
Period of Interest : 2013 - 2018					
Post x Treat	0.438***	0.683***	0.717***	0.589***	0.555***
	(0.157)	(0.174)	(0.175)	(0.147)	(0.147)
Observations	8,726	7,859	7,856	7,856	7,856
R-squared	0.022	0.025	0.157	0.179	0.181
Pre-treatment Period : 2003 - 2013					
Post x Treat	-0.0763	-0.0763	0.142	-0.277	-0.269
	(0.290)	(0.290)	(0.203)	(0.200)	(0.191)
Observations	7,043	7,043	6,864	6,864	6,864
R-squared	0.022	0.022	0.165	0.182	0.185
Individual Controls X_{ijmys}	Yes	Yes	Yes	Yes	Yes
PS Reweighting	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Birth Month FE	No	No	Yes	Yes	Yes
Birth Month x Birth Year FE	No	No	Yes	Yes	Yes
State FE	No	No	No	Yes	Yes
$POST_j$ x X_{ijmys}	No	No	No	No	Yes

Difference-in-difference estimations based on 2003 and 2013 DHS for the parallel trend, and on 2013 and 2018 DHS for the main period of interest.
The balance table 3.2 shows that the mean HAZ score for control children was -1.973 at the time of pre-treatment. Estimates from specification (5) can be interpreted as followed: children in treated areas benefit from a 28% health improvement proxied by HAZ score relatively to children from control areas.
The child is defined as treated if her community is less than 15 km to at least one orchard.
Standard errors in parentheses are clustered at the community level (DHS clusters).
*** p<0.01, ** p<0.05, * p<0.1

Table 3.4: Impacts of shelterbelts on children height-to-age z-score

	Shelterbelt treatment at 15 km				
	(1)	(2)	(3)	(4)	(5)
Period of Interest : 2013 - 2018					
Post x Treat	0.717**	0.862**	0.902***	0.537	0.514
	(0.348)	(0.378)	(0.328)	(0.364)	(0.355)
Observations	10,027	6,699	6,698	6,698	6,698
R-squared	0.021	0.020	0.148	0.153	0.155
Pre-treatment Period : 2003 - 2013					
Post x Treat	-0.295	-0.295	0.214	-0.251	-0.321
	(0.471)	(0.471)	(0.311)	(0.326)	(0.339)
Observations	8,204	8,204	3,718	3,718	3,718
R-squared	0.018	0.018	0.150	0.157	0.158
Individual Controls X_{ijmys}	Yes	Yes	Yes	Yes	Yes
PS Reweighting	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Birth Month FE	No	No	Yes	Yes	Yes
Birth Month x Birth Year FE	No	No	Yes	Yes	Yes
State FE	No	No	No	Yes	Yes
$POST_j$ x X_{ijmys}	No	No	No	No	Yes

Difference-in-difference estimations based on 2003 and 2013 DHS for the parallel trend, and on 2013 and 2018 DHS for the main period of interest.
The child is defined as treated if her community is less than 15 km to at least one shelterbelt.
Standard errors in parentheses are clustered at the community level (DHS clusters).
*** p<0.01, ** p<0.05, * p<0.1

Table 3.5: Impacts of orchards and shelterbelts on children dietary diversity score

	(1)	(2)	(3)	(4)	(5)
Orchard treatment at 15 km: 2013 - 2018					
Post x Treat	0.133	0.496*	0.502**	0.561***	0.560***
	(0.185)	(0.262)	(0.215)	(0.206)	(0.207)
Observations	8,109	7,281	7,273	7,273	7,273
R-squared	0.013	0.018	0.301	0.310	0.311
Shelterbelt treatment at 15 km : 2013 - 2018					
Post x Treat	0.381	0.539	0.117	0.0504	0.0395
	(0.304)	(0.391)	(0.253)	(0.286)	(0.292)
Observations	9,246	5,839	5,834	5,834	5,834
R-squared	0.013	0.019	0.332	0.335	0.337
Individual Controls X_{ijmys}	Yes	Yes	Yes	Yes	Yes
PS Reweighting	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Birth Month FE	No	No	Yes	Yes	Yes
Birth Month x Birth Year FE	No	No	Yes	Yes	Yes
State FE	No	No	No	Yes	Yes
$POST_j$ x X_{ijmys}	No	No	No	No	Yes

Difference-in-difference estimations based on 2013 and 2018 DHS.
Standard errors in parentheses are clustered at the community level (DHS clusters).
*** p<0.01, ** p<0.05, * p<0.1

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Conclusion

L'actualité nous rappelle tous les jours à quel point les moyens de subsistance actuels sont menacés par l'inexorable hausse des températures. La perspective d'un accroissement de la fréquence et de l'intensité des évènements climatiques extrêmes entrave les conditions d'existence des individus dépendant de ces paramètres pour vivre. Ce constat presse les décideurs politiques à agir pour accompagner les stratégies d'adaptation au changement climatique et atténuer la vulnérabilité des ménages ruraux. Si la recherche en économie ne cesse de produire d'importants travaux sur les différentes stratégies de gestion du risque et leurs répercussions sur le bien-être et la résilience des ménages, de nombreuses questions restent encore en suspens. Cette thèse espère ainsi contribuer à éclairer le débat autour de ces enjeux en compilant trois essais empiriques précedemment développés.

En mobilisant des enquêtes ménages et les outils de la microéconomie, cette thèse répond à trois questions restées encore largement inexplorées: (i) Comment les décisions d'investissement agricole dans les technologies d'adaptation au changement climatique sont-elles influencées par les mécanismes de mutualisation du risque? (ii) Quel est l'impact moyen et l'hétérogénéité des effets de traitement des programmes d'assurance indicielle sur les décisions de production agricole? (iii) Quelles sont les conséquences d'un programme de restauration environnementale sur la santé des enfants?

Les résultats mis en exergue dans chacun des trois chapitres s'accompagnent de recommandations de politique économique adaptées aux zones rurales et semi-arides des pays en voie de développement. Le chapitre 1 pointe les effets néfastes de certains mécanismes de mutualisation du risque qui peuvent conduire les agriculteurs à limiter leur investissement dans des technologies d'adaptation au changement climatique. Ce résultat rappelle aux décideurs politiques que s'il n'est pas accompagné par des outils de gestion du risque plus formels, le système de caution solidaire seul ne suffira pas à améliorer la résilience des agriculteurs. L'efficacité de programmes plus institutionnalisés peut cependant être très hétérogène d'une zone d'étude à une autre. Le chapitre 2 alerte ainsi les décideurs politiques sur la faible validité externe des effets de traitement des programmes d'assurance indicielle récemment mis en oeuvre dans plusieurs pays. Enfin, le chapitre 3 démontre que des activités de restauration environnementale visant à faire de la nature une source d'amélioration des conditions de vie locale ont toute leur place dans l'éventail des actions possibles pour atténuer la vulnérabilité des ménages en zone rurale.

En même temps qu'elle fournit des clefs de compréhension sur certains mécanismes de gestion du risque, cette thèse soulève plusieurs questionnements. Notamment, est-ce que les effets positifs de l'assurance indicielle sur certaines décisions d'investissement persisteront à plus long-terme? Quelles sont les caractéristiques contextuelles et propres à chacun des programmes qui génère autant d'hétérogénéité dans la magnitude et la direction de leur impact? Ou bien encore, peut-on espérer que d'autres pays que le Nigéria impliqués dans le programme de la Grande Muraille Verte bénéficient des mêmes retombées positives sur la santé et la sécurité alimentaire? De futurs travaux seront nécessaires pour appuyer la mise en oeuvre de politiques publiques ciblées et adaptées aux changements de ce monde.

Appendix

Appendix A

Appendix to Chapter 1

Table A1: Results of Interaction Models with GPC characteristics

	Incremental Adaptations		**Transformational**
	Total	SWC	**Adaptations**
N_h	-0.014***	-0.018***	-0.006
	(0.004)	(0.004)	(0.006)
Money transfers	-0.691	-1.753***	-0.648
	(0.422)	(0.590)	(0.458)
Help against climate change	0.15	-0.550*	0.681*
	(0.312)	(0.296)	(0.352)
Money transfers x N_h	0.033***	0.028**	0.019*
	(0.011)	(0.009)	(0.011)
Help against climate change x N_h	-0.004	0.001	-0.014***
	(0.004)	(0.003)	(0.004)
Money transfers x Help against climate change	-0.014	1.125	-0.235
	(0.555)	(0.692)	(0.481)
Money Transfers x Help against climate change x N_h	-0.021	-0.030**	-0.048***
	(0.016)	(0.013)	(0.016)
Controls	Yes	Yes	Yes
Fixed Effect for Cotton Zone	Yes	Yes	Yes
Fixed Effect for *Departements*	Yes	Yes	Yes
No. of Observations	660	660	660
Pseudo R^2	0.229	0.385	0.391

Standard errors clustered at village level in parentheses. Constant terms are not reported. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. GPC stands for "Group of Cotton Producers". N_h is the self-reported number of members. SWC stands for "Soil and Water Conservation Techniques". Control variables are still the following: mean distance, age, wealth index, education, early warning systems, lands, labour, rainfall, and temperature.

Table A2: Results of Interaction Models with GPC characteristics

	Incremental Adaptations		**Transformational**
	Total	SWC	**Adaptations**
N_h	-0.011**	-0.009**	-0.003
	(0.004)	(0.005)	(0.005)
Agricultural advice	4.654***	12.551***	1.392
	(0.564)	(0.702)	(0.906)
Help against climate change	0.159	-0.087	0.408
	(0.360)	(0.316)	(0.430)
Agricultural advice x N_h	-0.010*	-0.178***	-0.014
	(0.006)	(0.008)	(0.010)
Help against climate change x N_h	-0.007*	-0.009*	-0.015***
	(0.004)	(0.005)	(0.006)
Agricultural advice x Help against climate change	-5.800***	-13.449***	-1.474
	(0.708)	(0.639)	(0.991)
Agricultural advice x Help against climate change x N_h	0.064***	0.203***	0.037***
	(0.020)	(0.013)	(0.011)
Controls	Yes	Yes	Yes
Fixed Effect for Cotton Zone	Yes	Yes	Yes
Fixed Effect for *Departements*	Yes	Yes	Yes
No. of Observations	660	660	660
Pseudo R^2	0.225	0.385	0.354

Standard errors clustered at village level in parentheses. Constant terms are not reported. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. GPC stands for "Group of Cotton Producers".N_h is the self-reported number of members. SWC stands for "Soil and Water Conservation Techniques". Control variables are still the following: mean distance, age, wealth index, education, early warning systems, lands, labour, rainfall, and temperature.

Table A3: Results with new definitions of independent variable and dependant variable

	Incremental Adaptations (1)	Transformational Adaptations (2)	Transformational Adaptations (3)
Self-reported number of members			-0.011***
			(0.003)
Actual number of members	-0.021***	-0.027***	
	(0.004)	(0.005)	
Controls	Yes	Yes	Yes
Fixed Effect for Cotton Zone	Yes	Yes	Yes
Fixed Effect for *Departements*	Yes	Yes	Yes
No. of Observations	591	623	659
pseudo R^2	0.210	0.364	0.260

Standard errors clustered at village level in parentheses. Constant terms are not reported. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. GPC stands for "Group of Cotton Producers". Specifications (1) and (2) show the results with the alternative variable of interest, that is the actual number of members in the cooperative. Specification (3) introduces coefficients for a restrained definition of transformational adaptations. Control variables are still the following: mean distance, age, wealth index, education, early warning systems, lands, labour, rainfall, and temperature.

Table A4: Biprobit Model for Incremental and Transformational Adaptations

	Incremental Adaptations	Transformational Adaptations
Self-reported number of members	-0.015***	-0.014***
	(0.003)	(0.003)
Mean Distance	-0.017	-0.006
	(0.015)	(0.009)
Age	0.016***	0.001
	(0.005)	(0.004)
Wealth Index	-0.129***	-0.045
	(0.048)	(0.066)
Education	0.178	0.173
	(0.118)	(0.109)
Early Warning Systems	0.769**	1.601***
	(0.305)	(0.273)
Labour	0.003	0.005
	(0.004)	(0.005)
Lands	0.052	0.036
	(0.035)	(0.038)
Climate Environment:		
Rainfall Ratio	17.877*	-37.110***
	(10.634)	(13.434)
Average Temperature	-0.193	-0.448
	(0.219)	(0.305)
Fixed Effect for Cotton Zone	Yes	
Fixed Effect for *Departements*	Yes	
athrho	1.012***	
	(0.103)	
No. of Observations	660	

Standard errors clustered at village level in parentheses. Constant terms are not reported. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Wald test of rho=0: chi2(1) = 52.85 Prob > chi2=0.00.
Marginal effects for N_h: Pr(incre=1, transfo=1) = -0.003 ***

Table A5: Ordered Probit Model for Incremental and Transformational Adaptations

	Incremental Adaptations	Transformational Adaptations
Self-reported number of members	-0.009***	-0.008***
	(0.002)	(0.002)
Mean Distance	-0.025	-0.007
	(0.017)	(0.007)
Age	0.007	0.007*
	(0.005)	(0.004)
Wealth Index	-0.103**	-0.020
	(0.041)	(0.040)
Education	0.053	0.195**
	(0.095)	(0.092)
Early Warning Systems	0.901***	0.874***
	(0.319)	(0.184)
Labour	0.002	0.006
	(0.004)	(0.005)
Lands	-0.004	0.042
	(0.029)	(0.031)
Climate Environment:		
Rainfall Ratio	15.872*	-23.747*
	(8.168)	(12.130)
Average Temperature	-0.134	-0.281
	(0.172)	(0.198)
Fixed Effect for Cotton Zone	Yes	Yes
Fixed Effect for *Departements*	Yes	Yes
No. of Observations	660	660
pseudo R^2	0.146	0.151
Estimated Marginal Effects of N_h		
Zero strategy adopted	0.003***	0.003***
	(0.000)	(0.001)
One strategy adopted	0.001***	0.000
	(0.000)	(0.000)
Two strategies adopted	- 0.003***	- 0.001***
	(0.001)	(0.000)
Three or more strategies adopted		- 0.002***
		(0.001)

Standard errors clustered at village level in parentheses. Constant terms are not reported. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Regressions for Incremental and Transformational Adaptation to Climate Change

	Cluster at GPC level		**Robust Standard Errors**	
	Incremental Adaptations	Transformational Adaptations	Incremental Adaptations	Transformational Adaptations
Self-reported number of members	-0.014***	-0.014***	-0.014***	-0.014***
	(0.003)	(0.003)	(0.002)	(0.002)
Mean Distance	-0.014	-0.009	-0.014*	-0.009
	(0.009)	(0.010)	(0.010)	(0.010)
Age	0.016***	0.001	0.016***	0.001
	(0.005)	(0.004)	(0.005)	(0.005)
Wealth Index	-0.1139**	-0.049	-0.139**	-0.049
	(0.056)	(0.067)	(0.056)	(0.048)
Education	0.160	0.175	0.160	0.175
	(0.137)	(0.136)	(0.138)	(0.131)
Early Warning Systems	0.964**	1.623***	0.964***	1.623***
	(0.313)	(0.286)	(0.175)	(0.212)
Labour	0.003	0.005	0.003	0.005**
	(0.004)	(0.005)	(0.002)	(0.002)
Lands	0.061	0.043	0.061	0.043
	(0.046)	(0.043)	(0.044)	(0.040)
Climate Environment:				
Rainfall Ratio	22.020**	-38.859***	22.020**	-38.859***
	(11.231)	(14.700)	(10.133)	(10.162)
Temperature	-0.116	-0.536*	-0.116	-0.536**
	(0.234)	(0.283)	(0.224)	(0.212)
Fixed Effect for Cotton Zone	Yes	Yes	Yes	Yes
No. of Observations	660	660	660	660
Pseudo R^2	0.203	0.320	0.203	0.320

Standard errors are in parentheses. Constant terms are not reported. "GPC" stands for "Cotton Producers' Group". * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix B

Appendix to Chapter 2

Figure B1: The average effect of index insurance on production decisions τ (automatic priors)

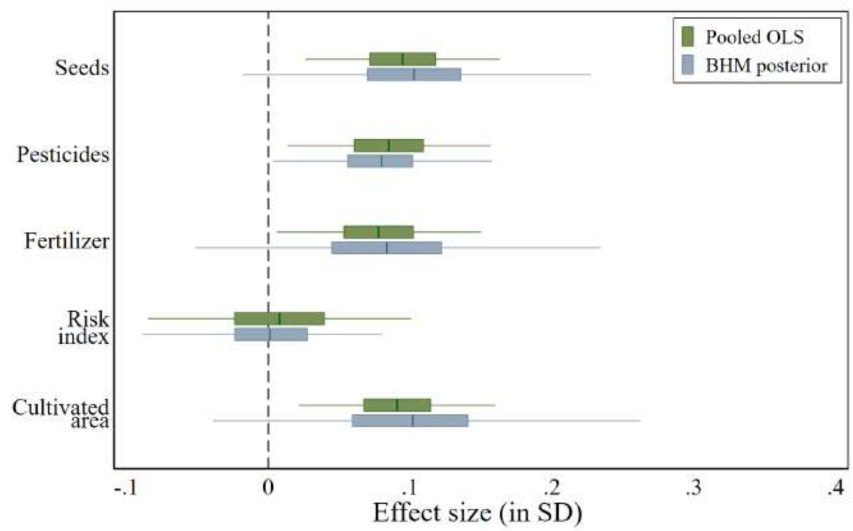
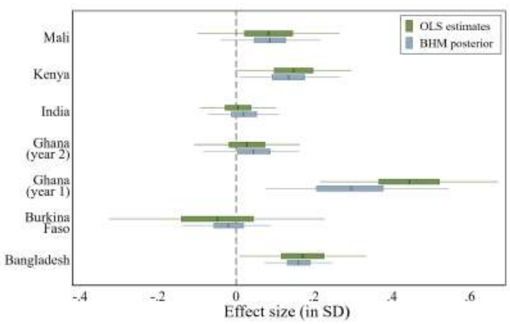
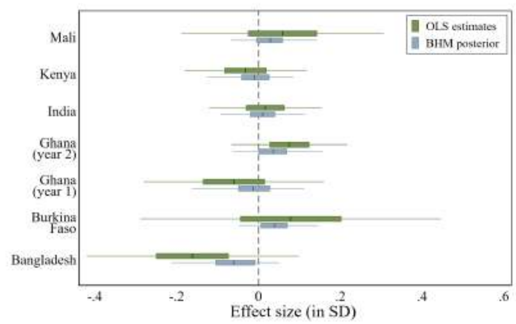


Figure B2: The heterogeneity of study-specific treatment effects τ_k (automatic priors)

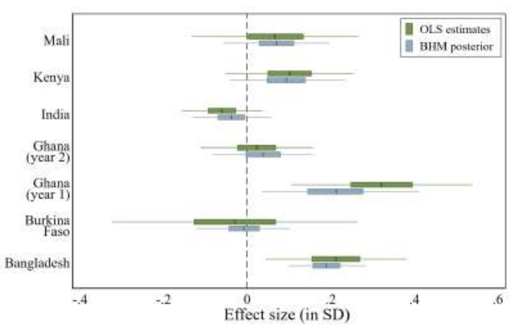
(a) Cultivated area



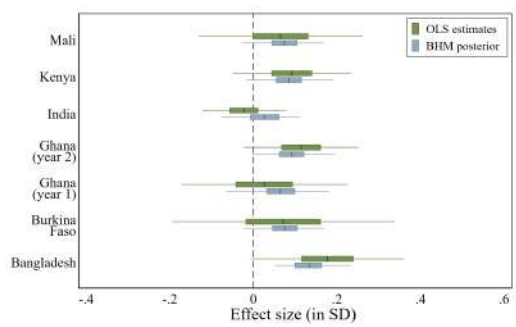
(b) Risk index



(c) Fertilizer



(d) Pesticide



(e) Seeds

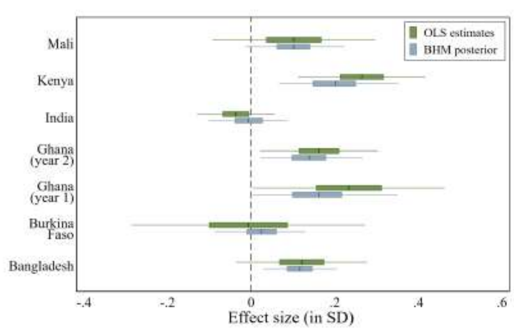
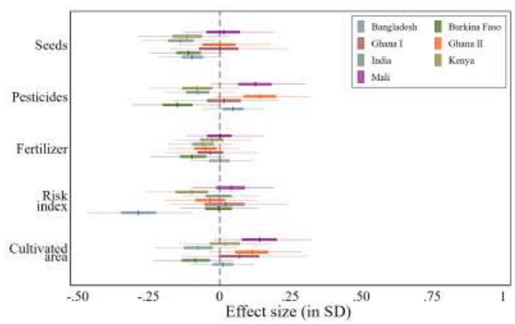
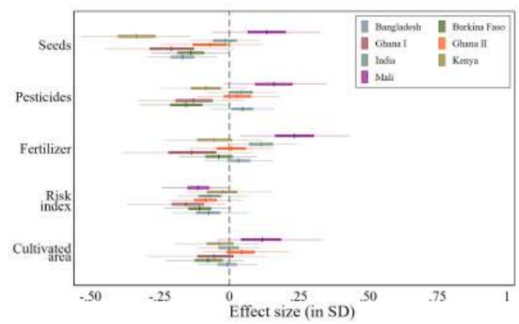


Figure B3: Estimates of study-specific treatment effects τ_k for all outcomes split by key co-variates

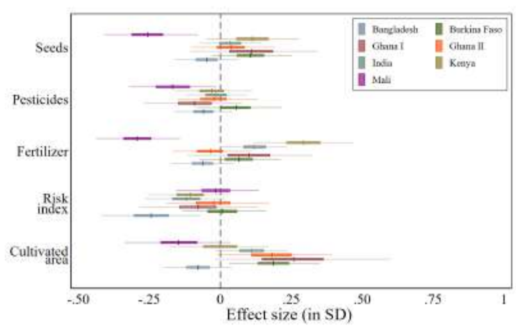
(a) Additional Effect when Wealth = High



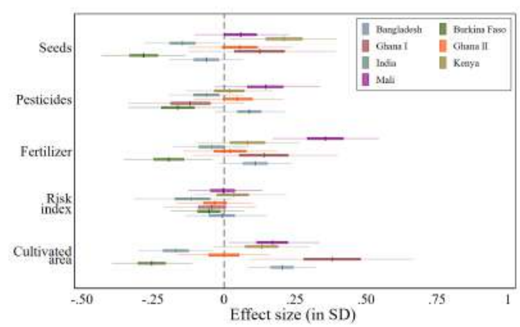
(b) Additional Effect when Age = High



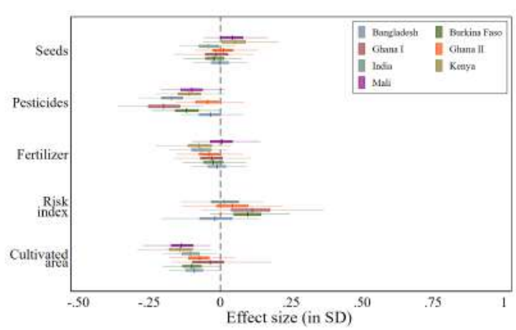
(c) Additional Effect when head is Literate



(d) Additional Effect when HH size = High



(e) Additional Effect when Predicted Outcome = High



(f) Effect when Price = High

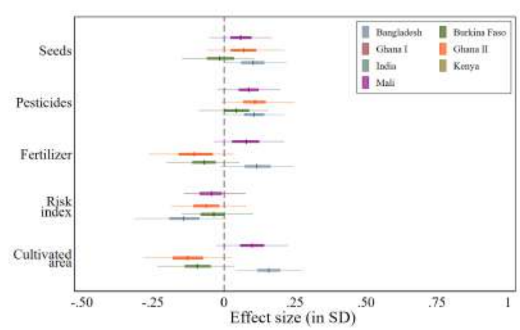


Figure B4: The predicted effect of index insurance in the next study τ_{k+1} (automatic priors)

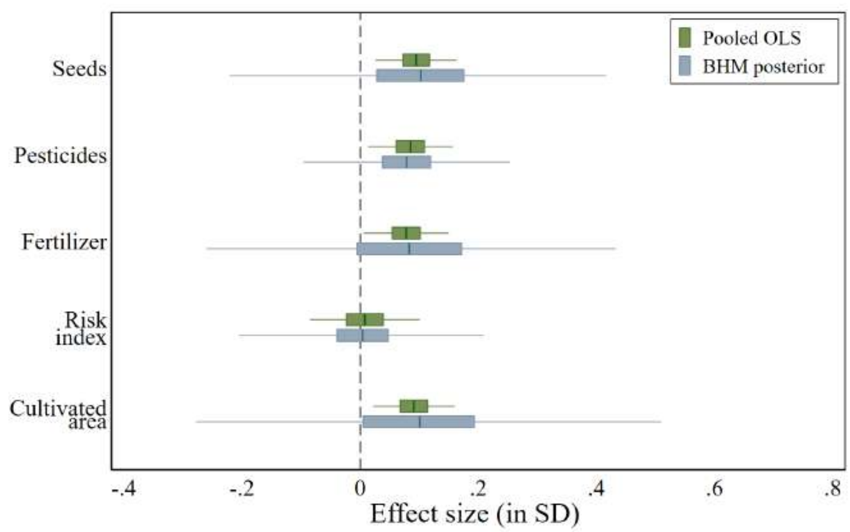


Figure B5: Estimates of τ_{k+1} for all outcomes split by key covariates

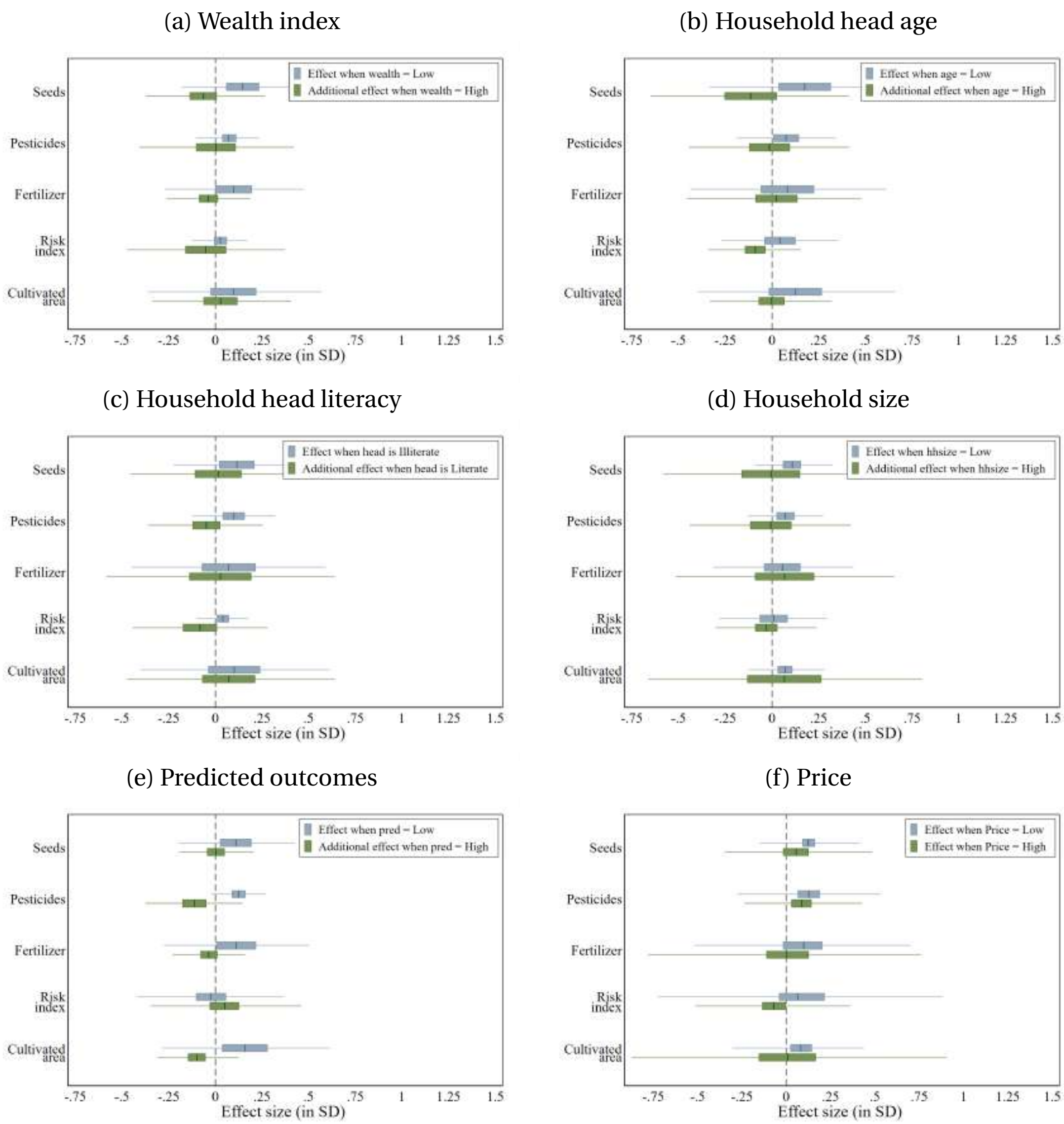


Table B1: Questions that will be used to derive outcomes

	Bangladesh	Burkina Faso	Ghana		India	India	Kenya	Mali
			Year 1	Year 2	(Cole et al.)	(Mobarak and Rosenzweig)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcomes[a]								
Cultivated area	E5	C1, D1.2, F1.3	H6	H8	E5	320, 322, 328	M7.1.1	H2, I3
Fertilizer use	E2C	D1.9-11, F1.9-11	L4-7	L4-7	E1.c-d	413-415, 430-431	M7.5.1	H6, H8, H9, I7, I9
Pesticide use	E2C	D1.12-13, F1.12-13	L4-7	L4-7	E1.e	434-436	M7.5.1	H10-11, I10-11
Seeds use	E17	D1.8, F1.8	K2	K3, K6	E1.a-b	405-408	M7.3	H5, I6
Crop portfolio riskiness[b]	E3	C10-23	H8	H9-10	E5	305	M7.1.1	I2

[a] We report the questions numbering from endline survey instruments provided by the authors. Mobarak and Rosenzweig (2013) have three endline survey instruments corresponding to the states of Andhra Pradesh, Tamil Nadu, and Uttar Pradesh. The codes for the outcomes are the same across survey and, thus, we write it only once. Althoug Mobarak and Rosenzweig (2013) and Hill et al. (2019) registered the outcomes for both dry and monsoon seasons, we analyze the outcomes for the monsoon (*Kharif*) season only.

[b] The crop portfolio risk index requires information on the type of crop that are cultivated on plots. Thus, codes identified here refer to questions about names of crops cultivated. When codes are redundant with *cultivated area*, it means that the distinction about crop types was already included in this question.

Table B2: Questions that will be used to derive covariates

	Bangladesh	Burkina Faso	Ghana		India	India	Kenya	Mali
			Year 1	Year 2	(Cole et al.)	(Mobarak and Rosenzweig)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Covariates[a]								
Age of the household head	A3	A1.4	1.5	B3	A4*	104.1	202	A4
Sex of the household head	A2	A1.1	1.2	B2	A3*	103	201	A2
Literacy of the household head[b]	A6	A1.6	2.c	C11-14	A6-7*	105	yrs_edu[c]	C1.6
Household size	A0	A2	1.1	B1	A1[d]	101	hhsize	C1.2
Wealth index[e]	H	H1	12.A-B	T	D1-2*	922-926*	M3*	E, E2
Predictors[f]								
Land ownership	C8	C1.21	7C	I	D6*	211	301	G1.5
Livestock units	H1-3	H2	7A	P	B*	901-909**	M3.4*	E3
Chemicals usage	E30	D1, F1,	7.I	L	A15	628-635**		
Bank account	L5		11A-C	X4	E1		401	
Attitude towards risk	L	T1, T2*			H			N
Years of schooling of the household head	A7	A2.25	2A-B	C4	A5*	105	yrs_edu	C1.6
Weather shock	K	D1.21, F1.22**	7N	N2.8		1302**		L5-6

[a] We report the questions numbering from baseline survey instruments provided by the authors. If not available, we report them from endline survey instruments and differentiate them with single asterisks.
[b] In Mobarak and Rosenzweig (2013), Elabed and Carter (2014) and Bulte et al. (2019), because there is no question on literacy, we proxy it using household head's years of schooling and divide the sample in two groups (above or below average years of schooling).
[c] This variable indicates the educational level of the respondent who is the main farmer in the household but not necessarily the head of the household.
[d] Household members below 6 years old are not registered.
[e] To compute the wealth index, we make use of the maximum of information available at the level study (durable assets owned by the household, housing and sanitary conditions) and refer to their variable codes here.
[f] Some of the predictors are already reported as covariates. If the predictors are not available in baseline questionnaires, we report them from endline survey instruments and differentiate them through single asterisk. When there are double asterisks, the variables are found in endline survey instruments but refer to the baseline period through recall questions.

The Bayesian Hierarchical model with and without household covariates

Consider some outcome of interest y_{ik} for an individual $i = 1,2,...N_k$ in study $k = 1,2....K$. Let Y_k represent the N_k-length vector of observed outcomes from group k. Denote the binary indicator of treatment status by T_{ik}, and denote by T_k the N_k-length vector of all treatment status indicators from group k

Suppose that y_{ik} varies randomly around its mean $\mu_k + \tau_k T_i$. τ_k is the treatment effect in group k. The random variation in y_{ik} may be the result of sampling variation or measurement error or it may be the result of unmodelled heterogeneity or uncertainty in outcomes for individuals within the group. We allow the variance of the outcome variable y_{ik} to vary across sites, so σ^2_{yk} may differ across k.

The evidence aggregation model from Rubin (1981) consists of a hierarchical likelihood as follows:

$$\begin{gathered} \hat{\tau_k} \sim N(\tau_k, \hat{se}_k^2) \\ \tau_k \sim N(\tau, \sigma_\tau^2) \end{gathered} \tag{B.1}$$

When we add covariates at the individual level like in Meager (2019), the model becomes:

$$\begin{gathered} y_{ik} \sim N(\sum_{p=1}^{2^L} [\mu_k^p + \tau_k^p T_{ik}] X_{ik}^{\pi(p)}, \sigma_{yk}^2) \\ \tau_k^p \sim N(\tau^p, \sigma_{\tau^p}^2) \end{gathered} \tag{B.2}$$

where X_{ik} is the covariate for household i in study k and L is the number of covariates included in the analysis. Overall, this results into 2^L intercept terms and 2^L slope terms indexed by p. Because X_{ik} are dummy variables, we obtain the bijection of the full set of interactions of these variables $\pi(p) : \{1,2,...,2^L\} \to \{0,1\}^L$. For $p \in \{0,1\}^L$, we consider $X_{ik}^p = \Pi_{p=1}^L [X_{ik}^p]^{\mathbb{1}\{I_p=1\}}$.

Bayesian estimation

The Bayesian estimation method makes draws from the joint posterior distribution $p(\{\tau_k\}_{k=1}^K, \tau, \sigma_\tau^2|y)$. We know from Baye's rule that $p(\{\tau_k\}_{k=1}^K, \tau, \sigma_\tau^2|y)$ is equal to $p(\{\tau_k\}_{k=1}^K|\tau, \sigma_\tau^2, y)p(\tau|\sigma_\tau^2,$
During the process of estimation, the hyperparameters σ_τ^2 and τ are successively drawn from their marginal posterior distributions and used to draw $\{\tau_k\}_{k=1}^K$ from

their posterior distribution.[1]

Given the equations for the posteriors, estimating the distributions of parameters relies on simulations. The Bayesian computation relies on the use of Markov chain Monte Carlo. For instance, consider s steps in the process of simulation. We first stimulate $\sigma_\tau^{2(s)}$ thanks to its distribution and compute $p(\sigma_\tau^2|y)$. $\sigma_\tau^{2(s)}$ then constitutes the input to calculate $p(\tau|\sigma_\tau^2, y)$ and get $\tau^{(s)}$ from its normal distribution. Eventually, $\tau^{(s)}$ helps to sample $p(\{\tau_k\}_{k=1}^K|\tau, \sigma_\tau^2, y)$ leading to independent $\tau_k^{(s)}$. It clearly appears that inferences on $\{\tau_k\}_{k=1}^K$ stem from inferences on (τ, σ_τ^2) and vice versa, propagating the underlying uncertainty at each step of the model (Betancourt and Girolami, 2013).

Pooling metrics

The conventional pooling factor The following equation, proposed first by Box and Tiao (1973), characterizes the main study-level pooling statistic:

$$\lambda_k^1 = \frac{\hat{se}_k^2}{\hat{se}_k^2 + \hat{\sigma}_\tau^2} \tag{B.3}$$

For each study k, this pooling metric shows the decomposition between the true heterogeneity across treatments captured by $\hat{\sigma}_\tau^2$ and sampling variation estimated by $\hat{se}_k^2$. Intuitively, when λ_k^1 becomes smaller, there is little chance that results from one context can inform us about the expected impacts in a new setting. $\lambda_k^1 > 0.5$ indicates a domination of sampling variation over true heterogeneity (Gelman and Hill, 2006). This conventional pooling factor is eventually averaged across studies and denoted $\lambda^1(\tau)$ and $\lambda^2(\tau)$.

The generalized pooling factor Gelman and Pardoe (2006) develops further the analysis to compute a "generalized pooling factor". Let E be the posterior mean and $\epsilon_k = \tau_k - \tau$. The generalized pooling factor follows:

$$\lambda = 1 - \frac{\frac{1}{K-1}\sum_{k=1}^K (E[\epsilon_k] - E[\bar{\epsilon_k}])^2}{E[\frac{1}{K-1}\sum_{k=1}^K (\epsilon_k - \bar{\epsilon_k}^2]} \tag{B.4}$$

Gelman and Pardoe (2006) also considers $\lambda > 0.5$ to be the threshold above which there is a higher degree of information at the "population level" rather than at the

[1](Gelman et al., 2013) describes the marginal posterior of the hyperparameters as $p(\tau, \sigma_\tau^2|y) \propto p(\tau, \sigma_\tau^2)\prod_{k=1}^K N(\hat{\tau}_k|\tau, \sigma_\tau^2 + \hat{se}_k^2)$. This can be simplified through integration over τ leading to $p(\tau, \sigma_\tau^2|y) = p(\tau|\sigma_\tau^2, y)p(\sigma_\tau^2|y)$ (see e.g. Bandiera et al., 2016).

“site level”. At the extreme value $\lambda = 0$, pooling data is not relevant since the broader population contains no information to the true effect in a specific context.

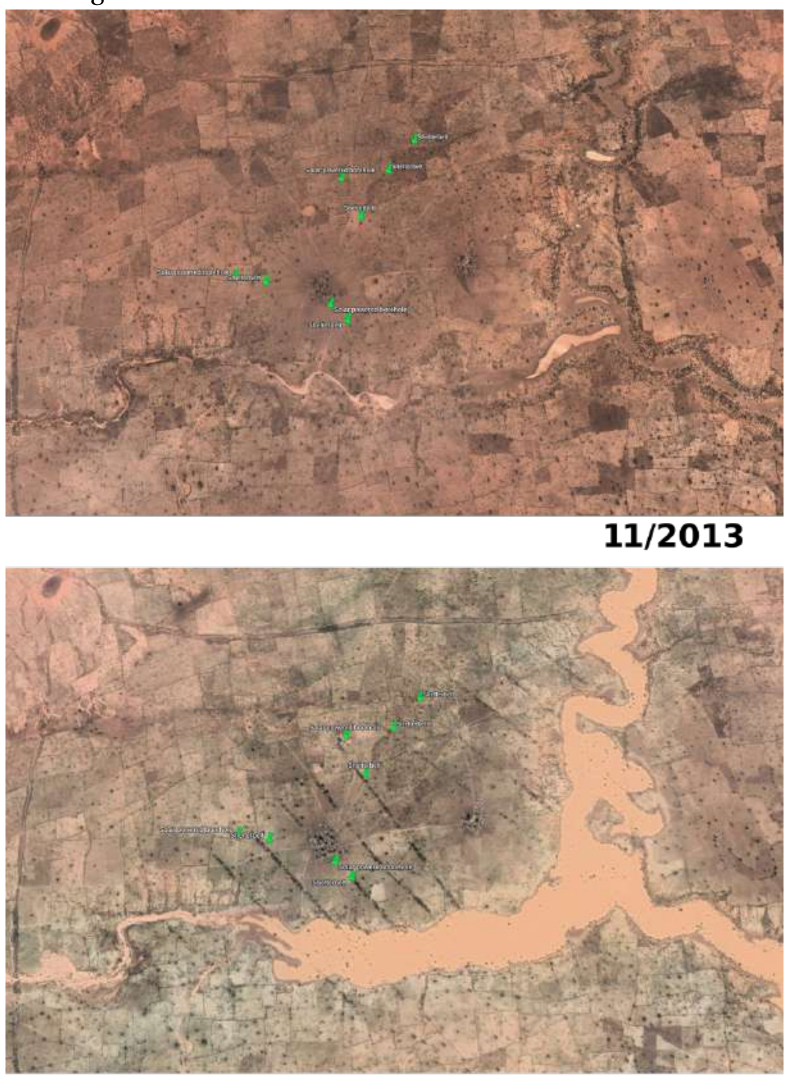
Appendix C

Appendix to Chapter 3

Table C1: Distribution of observations among treated and control groups in DHS surveys

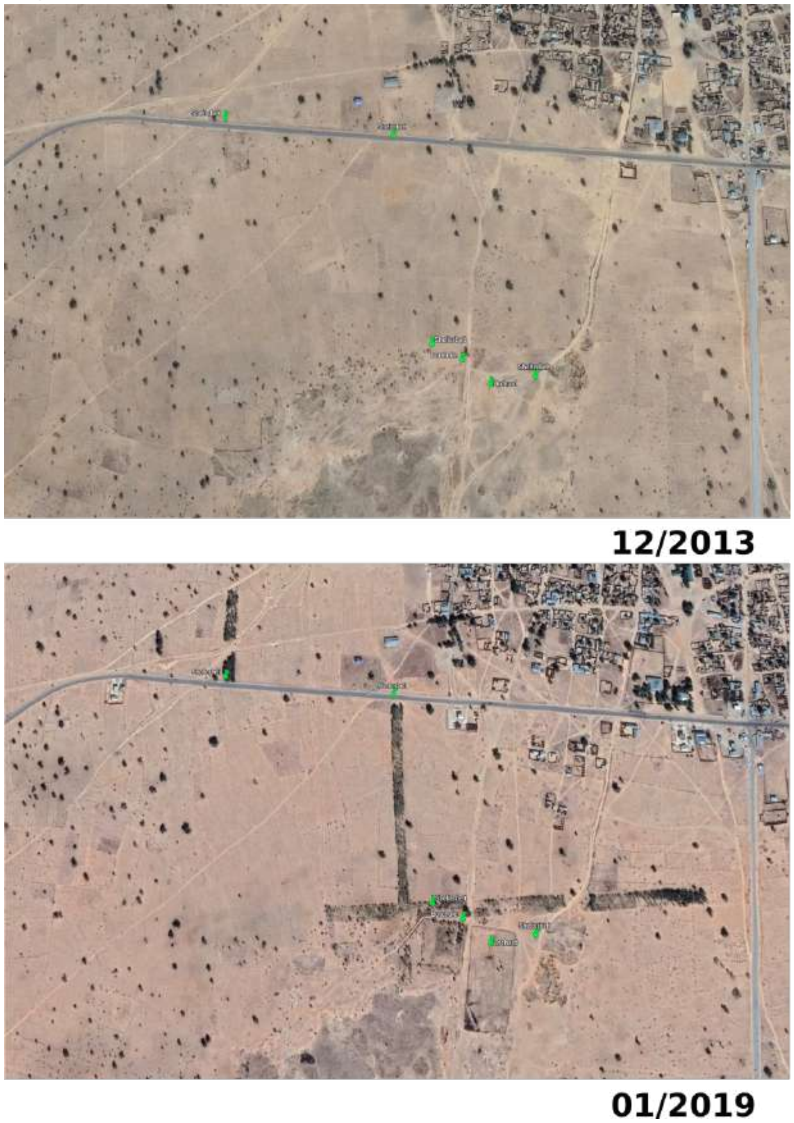
	10 km				15 km				20 km			
	2013		2018		2013		2018		2013		2018	
	Treated (after 2013)	*Control*	*Treated*	*Control*	*Treated* (after 2013)	*Control*	*Treated*	*Control*	*Treated* (after 2013)	*Control*	*Treated*	*Control*
Orchard	865	9,081	941	8,921	1,441	7,575	1,663	7,498	2,257	6,613	6,313	2,339
Total Sample	9,766		9,862		9,016		9,161		8,870		8,652	
Shelterbelt	197	10,530	326	10,329	447	10,097	472	9,522	808	8,867	931	8,665
Total Sample	10,727		10,665		10,544		9,994		9,675		9,596	

Figure C1: Satellite views of shelterbelts and boreholes



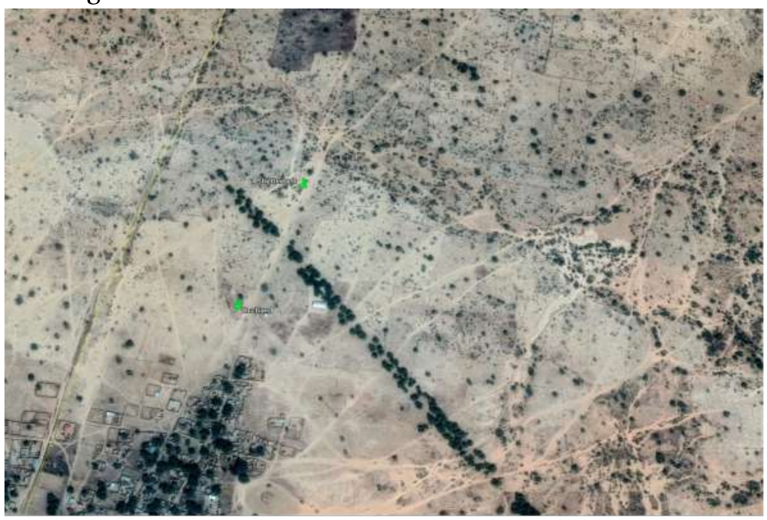
Two Google Earth views of Great Green Wall projects in Nigeria during the 2013-2020 period. Project in these views include 5 shelterbelts and 3 solar powered boreholes, which are observed during the winter, before (in 2013) and after (in 2020) their implementation (in 2015).

Figure C2: Satellite views of shelterbelts, boreholes and orchards



Two Google Earth views of Great Green Wall projects in Nigeria during the 2013-2020 period. Project in these views include 4 shelterbelts, a solar powered borehole and an orchard, which are observed during the winter, before (in 2013) and after (in 2019) their implementation (2014-2015).

Figure C3: Satellite views of shelterbelts and orchards



01/2014

11/2020

Two Google Earth views of Great Green Wall projects in Tumbo, Bachaka, Kebbi, Nigeria (on the border between Niger and Nigeria) during the 2013-2020 period. Project in these views include a shelterbelt and an orchard, which are observed during the winter, in 2014 and 2020

Table C2: Impacts of orchards and shelterbelts on children height-to-age z-score

	(1)	(2)	(3)	(4)	(5)
Orchard treatment at 15 km : 2013 - 2018					
Post x Treat	0.443***	0.715***	0.731***	0.599***	0.557***
	(0.162)	(0.174)	(0.177)	(0.149)	(0.148)
Observations	8,549	7,690	7,688	7,688	7,688
R-squared	0.022	0.025	0.157	0.179	0.182
Shelterbelt treatment at 15 km : 2013 - 2018					
Post x Treat	0.774**	0.978***	0.992***	0.624*	0.599*
	(0.356)	(0.330)	(0.314)	(0.354)	(0.341)
Observations	9,824	6,590	6,589	6,589	6,589
R-squared	0.021	0.023	0.149	0.154	0.157
Individual Controls X_{ijmys}	Yes	Yes	Yes	Yes	Yes
PS Reweighting	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Birth Month FE	No	No	Yes	Yes	Yes
Birth Month x Birth Year FE	No	No	Yes	Yes	Yes
State FE	No	No	No	Yes	Yes
$POST_j$ x X_{ijmys}	No	No	No	No	Yes

Difference-in-difference estimations based on 2013 and 2018 DHS.
All children belonging to households who migrated between 2013 and 2018 are excluded from the analysis.
Standard errors in parentheses are clustered at the community level (DHS clusters).
*** p<0.01, ** p<0.05, * p<0.1

Table C3: Impacts of orchards and shelterbelts on children height-to-age z-score

	(1)	(2)	(3)	(4)	(5)
Orchard treatment at 15 km : 2013 - 2018					
Post x Treat	0.411**	0.707***	0.769***	0.622***	0.583***
	(0.163)	(0.180)	(0.179)	(0.158)	(0.158)
Observations	7,105	6,567	6,566	6,566	6,566
R-squared	0.025	0.025	0.159	0.172	0.176
Shelterbelt treatment at 15 km : 2013 - 2018					
Post x Treat	0.769**	0.877**	0.929***	0.541*	0.556*
	(0.351)	(0.405)	(0.317)	(0.315)	(0.316)
Observations	5,945	4,754	4,754	4,754	4,754
R-squared	0.025	0.020	0.159	0.166	0.167
Individual Controls X_{ijmys}	Yes	Yes	Yes	Yes	Yes
PS Reweighting	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Birth Month FE	No	No	Yes	Yes	Yes
Birth Month x Birth Year FE	No	No	Yes	Yes	Yes
State FE	No	No	No	Yes	Yes
$POST_j$ x X_{ijmys}	No	No	No	No	Yes

Difference-in-difference estimations based on 2003 and 2013 DHS for the parallel trend, and on 2013 and 2018 DHS for the main period of interest.
All children living in communities more than 100 km away from an orchard or a shelterbelt are dropped from the analysis.
Standard errors in parentheses are clustered at the community level (DHS clusters).
*** p<0.01, ** p<0.05, * p<0.1

Table C4: Impacts of orchards on children height-to-age z-score

	Orchard treatment at 15 km				
	(1)	(2)	(3)	(4)	(5)
Period of Interest : 2013 - 2018					
Post x Treat	0.438***	0.532**	0.505***	0.459**	0.424**
	(0.157)	(0.209)	(0.162)	(0.183)	(0.178)
Observations	8,726	8,726	8,724	8,724	8,724
R-squared	0.022	0.022	0.152	0.163	0.166
Pre-treatment Period : 2003 - 2013					
Post x Treat	-0.0763	-0.0763	-0.165	-0.201	-0.0785
	(0.290)	(0.290)	(0.231)	(0.240)	(0.237)
Observations	7,043	7,043	5,594	5,594	5,594
R-squared	0.022	0.022	0.144	0.161	0.164
Individual Controls X_{ijmys}	Yes	Yes	Yes	Yes	Yes
PS Reweighting	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Birth Month FE	No	No	Yes	Yes	Yes
Birth Month x Birth Year FE	No	No	Yes	Yes	Yes
State FE	No	No	No	Yes	Yes
$POST_j$ x X_{ijmys}	No	No	No	No	Yes

Difference-in-difference estimations based on 2003 and 2013 DHS for the parallel trend, and on 2013 and 2018 DHS for the main period of interest.
The child is defined as treated if her community is less than 15 km to at least one orchard.
Standard errors in parentheses are clustered at the community level (DHS clusters).
*** p<0.01, ** p<0.05, * p<0.1

Table C5: Impacts of shelterbelts on children height-to-age z-score

	Shelterbelt treatment at 15 km				
	(1)	(2)	(3)	(4)	(5)
Period of Interest : 2013 - 2018					
Post x Treat	0.717**	0.544	0.591**	0.543*	0.554*
	(0.348)	(0.341)	(0.274)	(0.296)	(0.297)
Observations	10,027	5,624	5,621	5,621	5,621
R-squared	0.021	0.021	0.156	0.163	0.164
Pre-treatment Period : 2003 - 2013					
Post x Treat	-0.295	-0.295	-0.362	-0.332	-0.0979
	(0.471)	(0.471)	(0.379)	(0.415)	(0.413)
Observations	8,204	8,204	2,217	2,217	2,217
R-squared	0.018	0.018	0.157	0.159	0.161
Individual Controls X_{ijmys}	Yes	Yes	Yes	Yes	Yes
PS Reweighting	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Birth Month FE	No	No	Yes	Yes	Yes
Birth Month x Birth Year FE	No	No	Yes	Yes	Yes
Rainfall FE	No	No	No	Yes	Yes
$POST_j$ x X_{ijmys}	No	No	No	No	Yes

Difference-in-difference estimations based on 2003 and 2013 DHS for the parallel trend, and on 2013 and 2018 DHS for the main period of interest.
The child is defined as treated if her community is less than 15 km to at least one shelterbelt.
Standard errors in parentheses are clustered at the community level (DHS clusters).
*** p<0.01, ** p<0.05, * p<0.1

Table C6: Impacts of joint projects on children height-to-age z-score

	(1)	(2)	(3)	(4)	(5)
Joint Orchard/Borehole treatment at 15 km : 2013 - 2018					
Post x Treat	0.654**	0.728***	0.800***	0.591***	0.532**
	(0.253)	(0.229)	(0.230)	(0.211)	(0.210)
Observations	8,733	5,175	5,174	5,174	5,174
R-squared	0.022	0.027	0.146	0.170	0.173
Joint Shelterbelt/Borehole treatment at 15 km : 2013 - 2018					
Post x Treat	0.825***	0.390	0.661**	0.541	0.632*
	(0.202)	(0.326)	(0.328)	(0.354)	(0.349)
Observations	9,664	6,856	6,854	6,854	6,854
R-squared	0.023	0.031	0.187	0.190	0.192
Individual Controls X_{ijmys}	Yes	Yes	Yes	Yes	Yes
PS Reweighting	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Birth Month FE	No	No	Yes	Yes	Yes
Birth Month x Birth Year FE	No	No	Yes	Yes	Yes
State FE	No	No	No	Yes	Yes
$POST_j$ x X_{ijmys}	No	No	No	No	Yes

Difference-in-difference estimations based on 2013 and 2018 DHS.
Treatment assignment is defined as being closed (less than 15 km) to a Orchard project joint with a borehole or to a Shelterbelt Project joint with a borehole. Children living closed to orchard or shelterbelt projects alone are dropped from the analysis to avoid biased estimates.
Standard errors in parentheses are clustered at the community level (DHS clusters).
*** p<0.01, ** p<0.05, * p<0.1

Table C7: Impacts of orchards/shelterbelts/boreholes treatment on children height-to-age z-score

	orchards/shelterbelts/boreholes treatment at 15 km				
	(1)	(2)	(3)	(4)	(5)
Period of Interest : 2013 - 2018					
Post x Treat	0.407***	0.638***	0.675***	0.524***	0.489***
	(0.149)	(0.176)	(0.175)	(0.141)	(0.140)
Observations	8,812	7,956	7,954	7,954	7,954
R-squared	0.021	0.023	0.157	0.179	0.181
Pre-treatment Period : 2003 - 2013					
Post x Treat	0.0407	0.0407	0.298	-0.196	-0.183
	(0.287)	(0.287)	(0.206)	(0.198)	(0.194)
Observations	7,093	7,093	6,915	6,915	6,915
R-squared	0.021	0.021	0.161	0.177	0.179
Individual Controls X_{ijmys}	Yes	Yes	Yes	Yes	Yes
PS Reweighting	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Birth Month FE	No	No	Yes	Yes	Yes
Birth Month x Birth Year FE	No	No	Yes	Yes	Yes
State FE	No	No	No	Yes	Yes
$POST_j$ x X_{ijmys}	No	No	No	No	Yes

Difference-in-difference estimations based on 2003 and 2013 DHS for the parallel trend, and on 2013 and 2018 DHS for the main period of interest.
The child is defined as treated if her community is less than 15 km to at least one orchard, one borehole or one shelterbelt.
Standard errors in parentheses are clustered at the community level (DHS clusters).
*** p<0.01, ** p<0.05, * p<0.1

Table C8: Impacts of orchards and shelterbelts on other health outcomes

	FEVER	COUGH	DIARRHEA	WEIGHT-TO-AGE	WEIGHT-TO-HEIGHT
Orchard treatment at 15 km : 2013 - 2018					
Post x Treat	-0.0426	-0.0784	0.0131	-1.684	-0.489
	(0.0320)	(0.0593)	(0.0566)	(2.481)	(3.255)
Observations	9,159	9,141	9,178	8,883	8,882
R-squared	0.142	0.108	0.126	0.098	0.088
Shelterbelt treatment at 15 km: 2013 - 2018					
Post x Treat	-0.0482	0.0345	0.0870	5.379	3.508
	(0.0416)	(0.0871)	(0.0748)	(4.530)	(4.639)
Observations	7,779	7,770	7,793	7,558	7,556
R-squared	0.141	0.123	0.120	0.086	0.079
Individual Controls X_{ijmys}	Yes	Yes	Yes	Yes	Yes
PS Reweighting	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Birth Month FE	Yes	Yes	Yes	Yes	Yes
Birth Month x Birth Year FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
$POST_j$ x X_{ijmys}	Yes	Yes	Yes	Yes	Yes

Difference-in-difference estimations based on 2013 and 2018 DHS.
Standard errors in parentheses are clustered at the community level (DHS clusters).
*** p<0.01, ** p<0.05, * p<0.1

Figures C4 and C5 show that impacts may also depend on the age at treatment. They plot the residual of equation 3.1, specification (5) of Table 3.3 and 3.4, i.e. average height-for-age in clusters that are close to (less than 15 km) one kind of project type and of control clusters (far from, i.e. more than 30 km of a given project type).

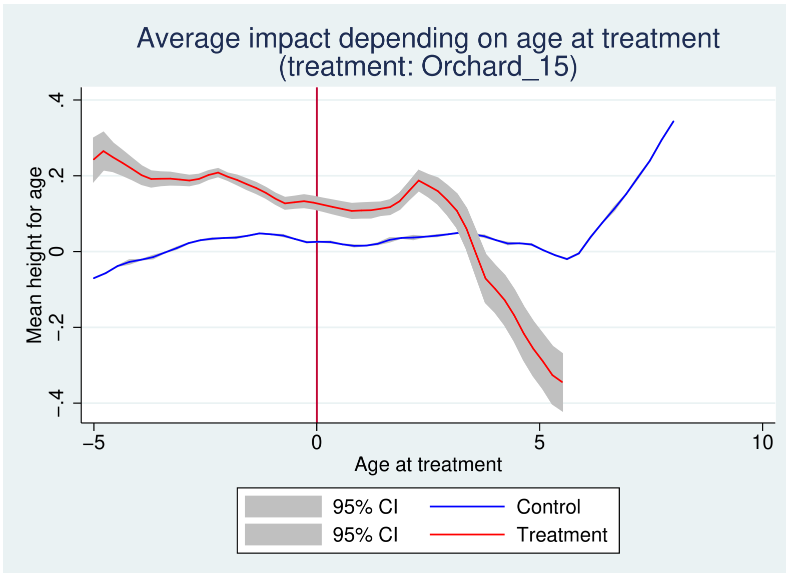


Figure C4: Kernel Weighted Local Polynomial Smooth of height to age for orchard treatment
Note: The graph depends on the age at treatment, ranging from 3 years before to 6 years after. The treatment group is drawn within 15 kilometres from the closest project (treatment), and the control group at more than 30 kilometres from the closest GGW project.

This analysis of heterogeneity in impact of treatments depending on the age at treatment reveals that most of the impact seem to occurs for younger cohorts of children: younger than 3 for shelterbelts and younger than 4 years old for orchards. This observation is coherent with evidence of a high sensitivity to food shortage and more generally to income shocks during early childhood (Hyland and Russ, 2019; Fishman et al., 2019; Maccini and Yang, 2009).

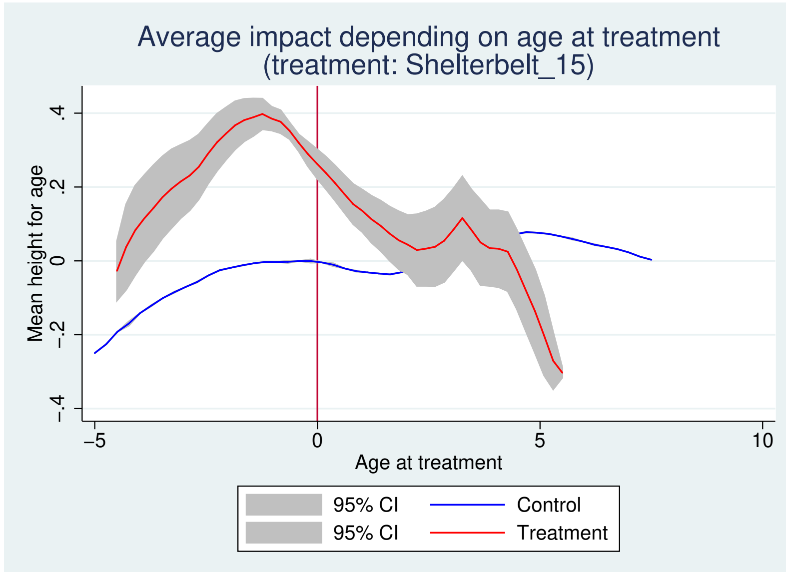


Figure C5: Kernel Weighted Local Polynomial Smooth of height to age for shelterbelt treatment

Note: The graph depends on the age at treatment, ranging from 3 years before to 6 years after. The treatment group is drawn within 15 kilometres from the closest project (treatment), and the control group at more than 30 kilometres from the closest GGW project.