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

Pauline Castaing[1] and Antoine Leblois[2]

[1]*CERDI, Université Clermont Auvergne*
[2]*CEE-M, INRAE, Montpellier*

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Abstract

This paper uses the implementation of Great Green Wall project in Nigeria as a quasi-natural experiment to document the local impact of environmental restoration on children's food security. Our identification strategy explores two types of variation to capture these effects. The spatial variation comes from the heterogeneous exposure of the children to these new greening areas. The temporal variation comes from sudden changes between 2013 and 2016. We find a significant 14% to 19% health improvement for children living next to community-based orchards and a 23% to 29% health improvement for children living next to new shelterbelts. Further results confirm that the observed increase in height-to-age occurs through the nutrition channel.

1 Introduction

Context In the 1970s and 1980s, severe droughts stroke Sub-Saharan Africa with terrifying consequences on local populations. These tragic events motivated the adoption of The United Nations Convention to Combat Desertification 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 biological productivity, land degradation damages livelihoods through food insecurity, water shortage, poverty, health problems and conflicts (Holden and Shiferaw, 2004; Couttenier and Soubeyran, 2014; Olagunju, 2015). Following the UNCCD 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 significantly improves livelihoods of the surrounding households is still an under-explored research question.

Forests are expected to have important consequences on welfare outcomes given the numerous ecosystem services that are at stake. There exists a growing body of evidence showing that forest-based ecosystem services are correlated to human well-being through diet quality, nutrition or health. Forests help improving household livelihoods through both direct and indirect channels. Direct reliance on ecosystem services refers to the capacity of the forests 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). Additionally, income-generating activities such as selling forest-based products or working in the conservation area are created consequently to the emergence of green areas (Newton et al., 2016). At last, forest resources can provide safety nets that help households absorb seasonal income shortfalls, periods of scarcity or environmental stress (Wunder et al., 2014). Many case studies bring evidence on the higher use of forest resources when a shock occurs, such as a crop failure, to complement the income or meet with subsistence

[1]The United Nations Convention to Combat Desertification defines desertification as "land degradation in arid, semi-arid and dry sub-humid areas resulting from various factors, including climate variation and human activities" (UNCCD, 1994).

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

needs (Pattanayak and Sills, 2001; McSweeney, 2005; Fisher et al., 2010). Regarding the indirect channels, crop lands benefit from forest-based environmental services through the supply of pollination, windbreak and nutrient cycling (Hajjar et al., 2008). Forests can also indirectly improve households health conditions by, for instance, filtering pollutants and pathogens or reducing exposure to malaria (Myers et al., 2013; Berazneva and Byker, 2017).

Although the literature on forest benefits is important, no study has analysed how the increase of vegetation cover during early stages of childhood may influence health outcomes. 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 (Glewwe et al., 2001) or health, educational and socio-economic achievements as adults (Maccini and Yang, 2009). 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. Therefore, the context in which the child begins her life deserves special attention. The 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 for Indonesian women. The environment when the child is in-utero also matters since prenatal exposure to negative shocks can result in lower birth weight with persistent effects (Almond and Currie, 2011; Lavy et al., 2016). While long-term impacts of food insecurity in early childhood have been well investigated, the literature lacks results about the extent to which individuals are able to mitigate these deficits using environmental restoration programs. To our knowledge, only social safety net programs have been investigated for their ability to help children coping with a harsh environment in early childhood (Gilligan et al., 2009; Dasgupta, 2017).

Contribution This article contributes to the existing literature on environmental restoration and children's welfare in a number of aspects. First, it is one of the first to document the local impact of environmental restoration on children's health outcomes. Although the interplay between deforestation and welfare outcomes is well investigated, there is surprisingly no literature on reforestation projects and their potential impacts on food security and health. 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 assess changes in food security of Nigerian households in order to identify potential drivers of children health improvement.

Identification Strategy To rigorously assess the impacts of environmental restoration on 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 children. The identification relies on the quasi-experimental variation in the greening activities implemented between late 2013 and 2016 in the northern regions of Nigeria. We draw from 2013 and 2018 Nigerian Demographic Health Survey (DHS) and their rich information about health status, in particular anthropometric measures for children. However, the main identification issue 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 placebo checks for the period preceding the GGW projects. This empirical methodology stays constant when we investigate the changes in households' nutrition, except that this assessment relies on Nigerian Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS - ISA).

Findings The findings are twofold. First, the children living next to areas where re-greening activities have been implemented appear to be in better health than control children. 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 by 14% to 19%. This health improvement goes up to 29% for children living nearby shelterbelt projects. Second, the nutrition intake of local households significantly and positively increases, bringing evidence that health improvement mainly occurs through better food access in the case of orchard treatment.

The remainder of the paper proceeds as follows. Section 2 introduces the context of the new environmental restoration program implemented in Nigeria as well as the data used in the analysis. Section 3 describes the identification strategy and section 4 displays the results. Section 5 concludes.

2 Context and Data

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 launched in 2007 to slow down the expansion of the Sahara (between 400 and 100 mm isohyets) by planting a barrier of trees spreading 7000 kilometers from Senegal to Djibouti.

Also represented as the "Sahel Greenbelt", the project implies regreening the Sahel region by planting trees over at least 15-km wide belt in order to tackle desertification, soil degradation and to mitigate atmospheric greenhouse gases emissions (Dia and Duponnois, 2010; Saley et al., 2019).

With the rising concerns about the climate change in 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 unprecented scale, providing food security, jobs and a reason to stay for the millions who live along its path".[3] To this end, more than height billion dollars have been mobilized and pledged for its support.

The project has been progressing at different scales among the eleven countries committed to give birth to the Greenbelt.[4] In Nigeria, the implementation of the project has been starting in 2013 with about 6,000,000 plants produced mainly for shelterbelts and community orchards. The program covers eleven frontline states along the northern border of the country. The National Council on the Great Green Wall (NCGGW) is the governing body deciding and monitoring the implementation of the program at the national level.

The implementation of the GGW project takes different forms in the country. Shelterbelts are rows of trees usually planted around fields to protect soil from erosion and improve the quality of farmlands. Between 2013 and 2016, 642 kilometers of such hedgerows

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

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

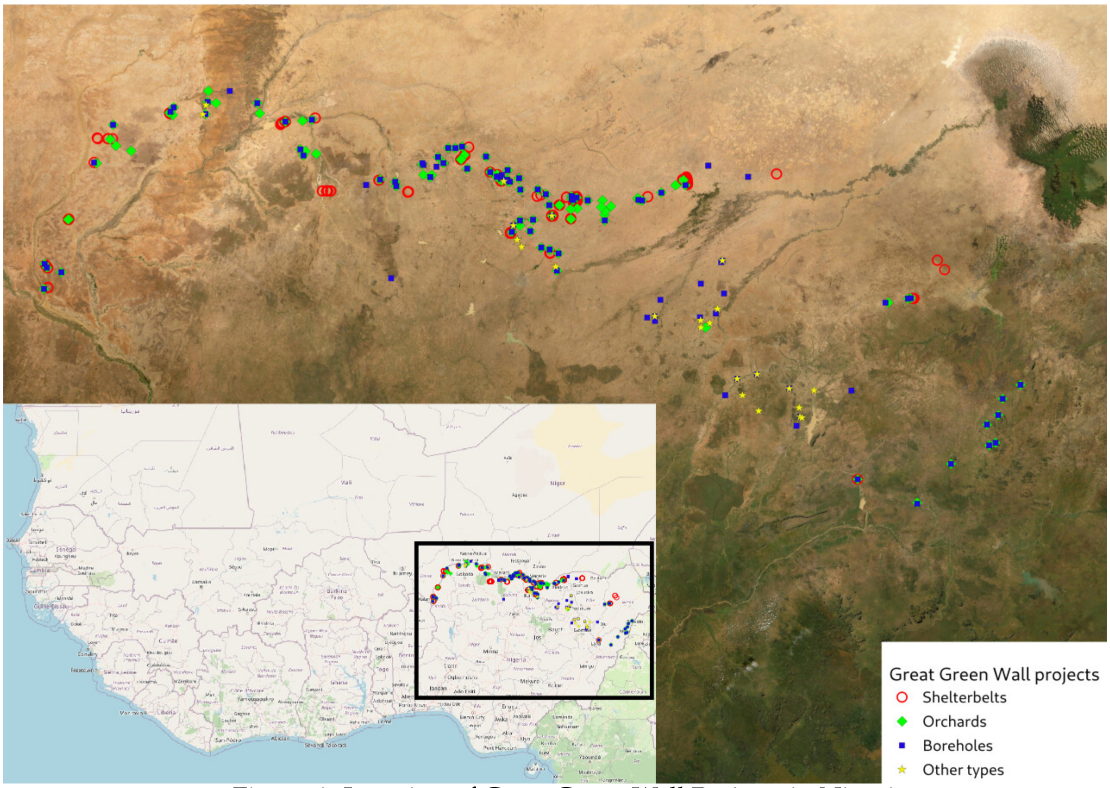

Figure 1: Location of Great Green Wall Projects in Nigeria

grew along the northern part of the country. About 300 hectares of community orchard have also been established to provide edible products to the local communities. A few projects also consists in providing fuelwood through new community woodlots. At least, about 156 solar and wind-powered boreholes have been constructed from late 2013 to 2016 to serve as water sources for households and their livestock. Given that features and interests associated with each greening activity differ, we decide to separately assess the impacts of orchards and shelterbelts on households' livelihood.

The data The main challenge to answer our research question is to locate the greening projects implemented through the Great Green Wall program. The National Council on the Great Green Wall provided us with precious information on the implementation and progress of the program on their territory since 2013. Geolocalisation of the activities, along with the type of the project, were made available for our research project. Figure 1 provides an overview of the different types of projects implemented on behalf of Great Green Wall program between 2013 and 2016.

2.2 Health of Nigerian Children

In this paper, the first 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 and state level. The data are geocoded at the DHS cluster level. For confidentiality issues, the DHS program displaces the latitude and longitude of the clusters. In rural areas in particular, they are moved by 0 to 5 kilometers, with 1 % of them displaced by up to 10 kilometers. We make use of data available for 2013 and 2018, two years surrounding the implementation of Great Green Wall projects. In order to perform placebo tests, DHS are also extracted for the year 2003.[5] We restrict our sample to rural households belonging to the eleven Northern States where Great Green Wall projects have been implemented.[6]

The primary sampling unit in the DHS is a cluster defined on the basis of enumeration areas from the 2006 Population Census Frame. All 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 Organisation (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 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 their distance to the GGW project, with a threshold established at 20 kilometers for the main specification. Among the children who are included in the analysis, approximately 20% are less than

[5] 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 Programme 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 programme is available here: www.fao.org/3/a-bd346e.pdf.

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

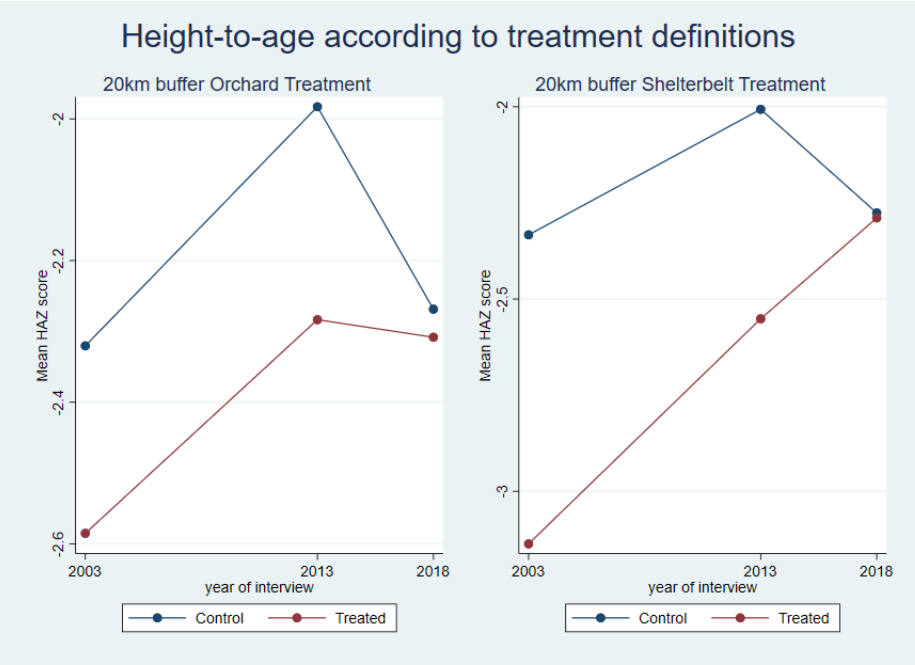

Figure 2: The evolution of height to age under two treatment definitions

20 kilometers far from a community-based orchard in 2018 whereas only 9% are close to a shelterbelt project (see Table 1). The figure 2 distinguishes children located close to an orchard or a shelterbelt project and shows their average HAZ score across the three waves of DHS.[7] 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 trends for both groups with higher worsening health conditions for control children (from -1.98 to -2.27, i.e. -15 %) than treated children (from -2.28 to -2.31, i.e. -1%). If we consider the shelterbelt projects, we see that health conditions has increased in the treated group (from -2.55 to -2.28, i.e. +11%) while it has decreased for the control group (from -2.01 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.

[7]The figure A1 in appendix introduces the trends when the average HAZ score from 2008 DHS is included.

2.3 Food Consumption of Nigerian Households

The second main source of socio-economic data helps investigating the role played by nutrition in children's health improvements. The medical and biological literature brings evidence that nutrition is the main channel through which physical growth operates (Grasgruber et al., 2014; Perkins et al., 2016). To capture food access and nutrition, the two most popular indicators are food consumption and calories intake. However, both are impossible to compute according to the narrow available information on nutrition intakes in the DHS. Therefore, we run the analysis of the underlying mechanisms with the use of an additional dataset that are the Nigerian LSMS-ISA.

The LSMS is a panel survey available for four waves (2010/2011 ; 2012/2013; 2015/2016 ; 2018/2019). However, the questionnaire for the last wave has been fully revised in comparison to previous years, making it too complicated to harmonize food security variables for our purpose. [8] For each round, the data collection follows a two-step process in line with the agricultural calendar, both after the planting season (September) and after the harvest season (March). This data represents a rich source of information for household food security and consumption aggregates. In total, about 5,000 Nigerian households are repeatedly questioned on their agricultural activities, other income activities, and household expenditures and consumption. Household location is geo-referenced with a coordinate modification strategy that follows the method developed by the DHS Program. The distance between the LSMS cluster and the GGW project helps us to determine the treatment status of the household, with a baseline threshold established at 20 kilometers. Again, we restrict our sample to the rural households living in the eleven states where some greening projects have been implemented.

Food consumption forms a common food access indicator, also more broadly used as a proxy for wealth status. It refers to the monetary value of the food consumed by the household on the last seven days, including both food purchased and food produced at home. [9] To take into account household size, food consumption is divided by the number of equivalent adults. Given that consumption measure may be subject to measurement error, we winsorize the variable at the bottom and top 1 % of the whole sample to prevent the results being driven by extreme values. Eventually, calories intake would have been

[8] Moreover, after almost a decade of visiting households, a big refresh of the sample was conducted for the fourth wave, with new enumeration areas. Due to security reasons, rural areas of Borno state were fully excluded from the refresh sample. Given that this state is part of our focus, it compromises the representativeness of the data.

[9] The food consumption variable is directly computed by the LSMS team. The general principle of valuation of food consumption is to use unit values, derived from reported purchases, and quantities consumed from all sources (purchased and own production).

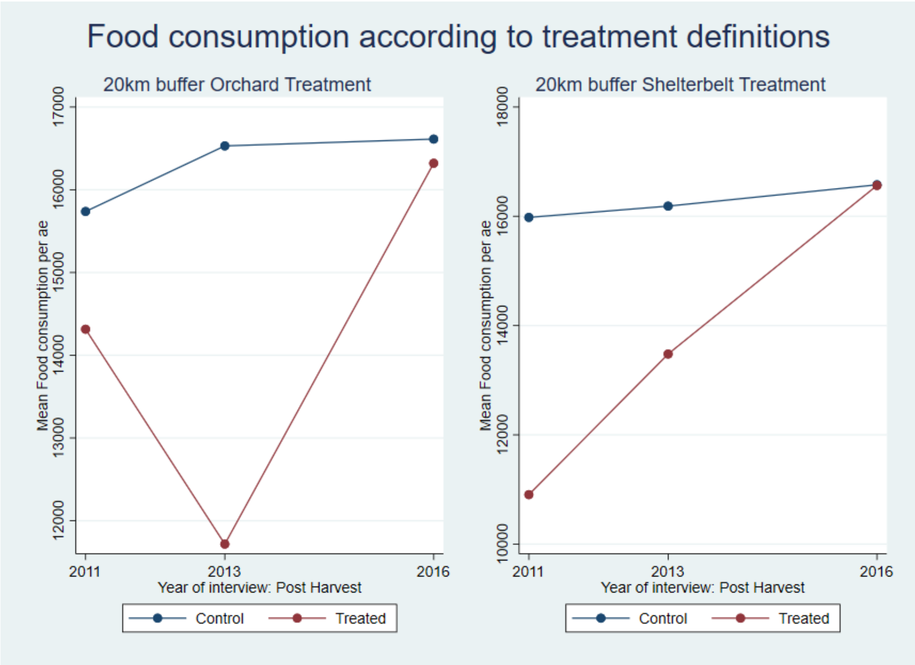

Figure 3: The evolution of food consumption under two treatment definitions

a reliable indicator for nutrition (Steckel, 1983). Unfortunately, Nigerian LSMS-ISA suffer from large measurement errors due to the lack of conversion factors for the food quantity units of measure used in the survey, preventing us from assessing the calories intake.

Given that the post-planting period of the third LSMS wave was conducted during the GGW implementation, that is 2015, we focus on the post-harvest visit to avoid any period of overlap. In 2016, 13% of the households are treated by the implementation of an orchard project whereas 9% lives close to a shelterbelt activity. Figure 3 displays the evolution of the winsorized food consumption across three post-harvest waves of LSMS. From 2013 to 2016, that is the time window when GGW projects were implemented, the average food consumption increases for both treated and control households. In particular, households treated by community-based orchards catch up the low food consumption they experienced in 2013.

Table 1: Distribution of Observations among Treated and Control Groups

	DHS				LSMS			
	2013		2018		2013		2016	
	Treated	*Control*	*Treated*	*Control*	*Treated*	*Control*	*Treated*	*Control*
Orchard	2,257	9,081	2,339	8,921	280	2,065	278	1,909
Shelterbelt	808	10,530	931	10,329	199	2,146	202	1,985
Total Sample	11,338		11,260		2,345		2,187	

3 Empirical Framework

The evolution of Great Green Wall implementation and re-greening of the Sahel offers an ideal quasi-natural experiment to better capture how environmental restoration programs may enhance health for children. The implementation of the project falls into the definition of quasi-natural since the targeted population is not randomly assigned. Indeed, the project focuses on specific areas where vegetation is already scarce and where there is a big room for food security improvements. This quasi-natural experiment is then subject to concerns regarding its internal validity because the treatment and the control group may not be comparable at baseline. To mitigate this risk and motivate our analysis, we provide several statistical tests.

The goal of this empirical study is to identify how the Great Green Belt enhances rural livelihoods for the local communities. To this end, we explore variations across time (the regreening period) and space (children distance to greenbelt projects provides). This actually refers to a double difference methodology, also called Difference-in-Difference (DiD). To do so, it is crucial to determine a treated and a control group at best.

We identify the locations of Great Green Wall projects by referring to the census of the projects and their GPS coordinates registered at the National Agency. In our baseline specification, we use a 20-kilometer buffer to distinguish treated and non-treated children. We believe that a buffer of 20 kilometers radius carries the dual benefit of being narrow enough to capture treated households while limiting the error in measurement induced by geographic displacement procedure on DHS clusters. In a robustness check, we exclude from the analysis all the children who are between 20 and 40 kilometers far from a project in order to rule out the risk that treated children are assigned to the control group.

Once we have determined if households are treated or not, we rely on DiD methodologies to assess the impact of the treatment on children's height-to-age. 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 :

$$Y_i = \alpha + \beta POST_i.TREAT_i + \gamma POST_i + \delta TREAT_i + \nu X_i + \theta X_i.POST_i + \epsilon_i. \tag{1}$$

with Y_i being the anthropometric measurement for child i whereas $POST_i$ and $TREAT_i$ are indicators for being in the post-treatment period and for the treated unit respectively. β 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. X_i include socio-demographic covariates such as sex and age of the head of the household, the size of the household, 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. $POST_i$ and X_i are also interacted for sensitivity checks.

Propensity Score Reweighting The empirical framework is subject to some limits for which the literature suggests remedies. In this quasi-natural experiment, the decision on the location of the project is certainly not random. The table A1 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 $p_i = P(TREAT_i = 1)$, is computed based on the set of covariates X. [10] Using this probability, we derive weights $\frac{1}{1-p_i}$ and $\frac{1}{p_i}$ assigned to non-treated and treated observations respectively. [11] The table A3 in appendices introduce the determinants of the treatment assignment.

Placebo Checks The placebo estimations aim at checking whether treated and control children had similar health trends before the regreening period. Two pre-treatment waves are available to check for Placebo Tests. It allows to build a credible counterfac-

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

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

tual for the control group and tests if any difference occurs during the placebo period. We do so by replicating the baseline estimations on the Placebo Period 2003-2013, with the difference that children from 2013 DHS wave are considered to belong to the post-treatment period ($POST_i = 1$). Given that several projects related to food security and agricultural productivity have been implemented on local households between 2003 and 2006, the average height-to-age of the children from the 2008 DHS displays an important increase for both treated and control groups (A1). We therefore decide to run the main placebo analysis on the period 2003-2013 to prevent bias on the results but still display the placebo estimates for the period 2008-2013.

Triple Difference We exploit the heterogeneity of the results by conducting a triple difference analysis. The age of children is used to define an extra control group. We consider that age of children is a gradual filter in terms of exposure to the projects. In particular, children who are less than two years old are considered as controlled given that no new project was implemented between 2016 and 2018. Those new-born children might have been less exposed to the projects given that the implementation of the projects in its early-stage requires more labor force and generates more income for the surrounding households. They may be an heterogeneity in the magnitude of the treatment if children are treated during the very beginning of the project, or later. Therefore, we create an additional dummy, Age_i, equal to 1 if the child is more than two years old, and interact this new term with other main variables ($POST_i$ and $TREAT_i$).

Channels Investigation Eventually, we use the same DiD methodology to investigate the change in food access for LSMS surveyed households. This time, the unit of observation i is the household, and covariates X_i include the age and sex of the household head, the size of the household, and the rainfall during the wettest quarter during the year previously to the survey. The balance table for treated versus control households A2 displays significant differences for characteristics at baseline in terms of rainfall. We tackle again this identification issue with the use of the IPW method and placebo checks.

4 Results

4.1 Main results

All the tables from this section are split between the panel with children surveyed for the period of interest and the children surveyed during the placebo period. Table 2 displays the results of the DiD estimation of the orchard 20 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 specifications. The coefficients range from 0.28 to 0.37 according to the specification at stake, meaning that one new orchard project created in a 20 km buffer around a cluster increases by 14% to 19% the health of children in treated areas relatively to children from other areas.[12] The stronger and higher estimate corresponds to the propensity score reweighting specification, for which each children has been associated to its probability to be treated. The placebo estimations aim at checking whether treated and controlled children had similar health improvement trends before their exposure to environmental restoration projects. The lower panel in 2 shows that none of the placebo estimates of β 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.

Table 3 displays the results for the DiD estimation for the other treatment assignment, that is the proximity to shelterbelt projects. The magnitude of the impact of this greening activity on children's health is higher and significantly positive across all specifications. The coefficients show a 23% to 29% increase in HAZ score of treated children in comparison to their controlled counterparts.[13] The treatment simulated on the placebo period shows that children's health was not following a positive trend for the children who were about to experienced the creation of GGW projects nearby. The placebo estimates show no significant results, bringing evidence that the trend captured during the actual treatment period was not already existing before.

Table A4 in appendix introduces the coefficients when the treatment definition includes all type of projects together, such as orchards, shelterbelts, woodlots or boreholes. Overall, the proximity to GGW projects significantly enhances HAZ scores by 15 % to 21% across specifications.[14] Tables A5 and A6 show that restricting the control groups to

[12]This effect is relative to the pre-treatment control group mean HAZ score, that is -1.983 in 2013.
[13]This effect is relative to the pre-treatment control group mean HAZ score, that is -2.007 in 2013.
[14]This effect is relative to the pre-treatment control group mean HAZ score, that is -1.983 in 2013.

Table 2: DiD regressions on height-to-age for Orchard Treatment

	Orchard Treatment				
	(1)	(2)	(3)	(4)	(5)
Period of Interest : 2013 - 2018					
Post x Treat	0.284**	0.275**	0.275**	0.339***	0.374***
	(0.134)	(0.134)	(0.135)	(0.129)	(0.132)
Observations	10,896	10,896	10,896	10,896	10,896
R-squared	0.021	0.022	0.032	0.152	0.151
Placebo Period : 2003 - 2013					
Post x Treat	-0.00370	-0.0428	-0.0690	0.000763	-0.0567
	(0.223)	(0.228)	(0.221)	(0.214)	(0.198)
Observations	8,871	8,871	8,871	8,871	8,871
R-squared	0.020	0.021	0.035	0.149	0.149
Individual Controls X_i	Yes	Yes	Yes	Yes	Yes
$POST_i$ x X_i	No	Yes	Yes	Yes	Yes
Birth Month FE	No	No	Yes	No	No
Birth Month x Birth Year FE	No	No	No	Yes	Yes
PS Reweighting	No	No	No	No	Yes

Difference-in-difference estimations based on 2003, 2013 and 2018 DHS. The child falls into the treatment group if she's less than 20 kilometers far from an orchard project.

Standard errors in parentheses are clustered at the village level.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: DiD regressions on height-to-age for Shelterbelt Treatment

	Shelterbelt Treatment				
	(1)	(2)	(3)	(4)	(5)
Period of Interest : 2013 - 2018					
Post x Treat	0.519**	0.512**	0.524**	0.582**	0.467*
	(0.241)	(0.242)	(0.241)	(0.234)	(0.261)
Observations	10,896	10,896	10,896	10,896	10,896
R-squared	0.020	0.021	0.031	0.151	0.151
Placebo Period : 2003 - 2013					
Post x Treat	0.142	0.178	0.101	0.208	0.222
	(0.442)	(0.472)	(0.482)	(0.402)	(0.441)
Observations	8,871	8,871	8,871	8,871	8,871
R-squared	0.019	0.020	0.035	0.148	0.148
Individual Controls X_i	Yes	Yes	Yes	Yes	Yes
$POST_i$ x X_i	No	Yes	Yes	Yes	Yes
Birth Month FE	No	No	Yes	No	No
Birth Month x Birth Year FE	No	No	No	Yes	Yes
PS Reweighting	No	No	No	No	Yes

Difference-in-difference estimations based on 2003, 2013 and 2018 DHS. The child falls into the treatment group if she's less than 20 kilometers far from a shelterbelt project.
Standard errors in parentheses are clustered at the village level.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

children who are more than 40 kilometers far from a project does not affect the strength of the results. Eventually, tables A9 and A10 bring evidence that the placebo estimates are statistically different from zero if we consider the 2008-2013 time window. During this period, children living in the area that would later be exposed to the greening projects suffered from a decrease in their height-to-age standard deviations, altering the parallel trend assumption that should precede the treatment.

Heterogeneity in the impact We carry out a triple difference analysis using the age of the children to capture heterogeneity in the treatment. In Table 4, the first two columns display the results when we study heterogeneity in the age of the children. $POST$ x $TREAT$ captures the treatment effect for the children less exposed to the treatment (orchard or shelterbelt), in other words the children who are less than two years. *Post* x *Treat* x *Age* reports the coefficient for the oldest children and is the main coefficient for triple difference (Age=1 when they are more than 2 years old). Coefficients for health improvement are not significant any more for the youngest children less exposed to the orchard or shelterbelt activities. For the oldest children living next to an orchard implementation, the coefficient is significant at 1% level and almost twice as big as the coefficient for the basic DiD regressions in table 2. Put it another way, children who were born during the period when community-based orchards started to be implemented experienced an increase in health improvement by 34%. The same coefficient is not significant for children exposed to shelterbelt projects. These overall results, and in particular the strong and significant positive impact of orchard projects on children born before 2016, drives us to further investigate the driver of such health improvement between 2013 and 2016.

4.2 Channels

The previous results show to which extent the impact of the project plays a key role for health improvement for children who were born before 2016, in particular when community-based orchards are at stake. As detailed above, we consider that nutrition and food intake in early stages of life is a determining factor in health status. Therefore, we rely on LSMS to study if health improvement is driven by some changes in post-harvest food consumption from the households who are living next to GGW projects. In addition to assessing the change in overall food consumption, we disentangle the changes in purchased food from the changes in food produced at home.

Table 5 displays the impact of the implementation of an orchard project on food consumption winsorized at 1% level for both the period of interest and the placebo period.

Table 4: Triple Difference regressions for Height to Age

Heterogeneity in :	Age	
	Orchard Treatment	Shelterbelt Treatment
Period of interest: 2013 - 2018		
Post x Treat x Age	0.565***	-0.0957
	(0.194)	(0.323)
Post x Treat	0.0136	0.640*
	(0.177)	(0.345)
Observations	10,906	10,906
R-squared	0.153	0.151
Individual Controls X_i	Yes	Yes
$POST_i$ x X_i	Yes	Yes
Birth Month x Year FE	Yes	Yes

Standard errors in parentheses are clustered at the village level.
*** p<0.01, ** p<0.05, * p<0.1
Age is a dummy equal to 1 if children are between 2 and 5 years old. The dummy equals 0 when the child is younger. The triple difference model includes all the interactive variables between Age_i, $POST_i$ and $TREAT_i$.

Across all specifications, the households who are exposed to an orchard project significantly increase their level of total food consumption. In particular, treated households increased their total food consumption by 41% to 45% according to the specification.[15] The increase in total food consumption is mainly driven by higher access to outside sources of food, with two possible interpretations. The first hypothesis depicts a direct channel, that is the higher access to edible products provided by the orchards itself. The second hypothesis is more indirect and involves the labor market. The idea is that household members were employed to work on community-based orchards, thus enjoying additional income that could be spent on food markets. The coefficients related to the placebo period brings evidence that this positive change didn't hold on before the implementation of GGW projects. When the main variable of interest is not winsorized, results still bring evidence of an important and significant increase in food consumption associated to the orchard treatment and holding only for the period of interest (Table A7).

Tables 6 and A8 display no significant changes in food consumption between the households who are exposed to shelterbelt projects and those who are not. This result makes sense given that shelterbelt projects do not directly provide new edible products to the local populations. Shelterbelts are mainly created to protect crop areas from soil erosion and improve agricultural productivity. This eventually may result in higher food security for households, but this needs to be observed on a longer run before drawing any conclusion on the efficiency of shelterbelt projects.

[15]This effect is relative to the pre-treatment control group mean food consumption for the post-harvest period, that is 17,091 NGN in 2013.

Table 5: DiD regressions for Food consumption for Orchard Treatment

	Orchard Treatment								
	Total food consumption			Home food consumption			Purchased food consumption		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Period of Interest : 2013 - 2016									
Post x Treat	7,067**	7,220**	7,691**	1,308	1,375	1,245	5,566*	5,662**	6,254**
	(3,504)	(3,266)	(3,404)	(1,126)	(1,135)	(1,121)	(2,937)	(2,825)	(3,022)
Observations	2,258	2,258	2,258	2,258	2,258	2,258	2,258	2,258	2,258
R-squared	0.203	0.225	0.226	0.156	0.162	0.162	0.164	0.188	0.189
Placebo Period : 2011 - 2013									
Post x Treat	-4,435	-4,509	-4,778	499.3	323.2	375.1	-4,897	-4,828	-5,137*
	(3,282)	(3,172)	(3,134)	(873.3)	(829.0)	(865.5)	(3,001)	(3,025)	(2,989)
Observations	2,379	2,379	2,379	2,379	2,379	2,379	2,379	2,379	2,379
R-squared	0.253	0.255	0.256	0.145	0.154	0.155	0.221	0.223	0.225
Household Controls X_i	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$POST_i$ x X_i	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
PS Reweighting	No	No	Yes	No	No	Yes	No	No	Yes

Difference in difference estimations based on 2011, 2013 and 2016 post-harvest LSMS. The household falls into the treatment group if it is less than 20 kilometres far from an orchard project. The weights for IPW are computed from covariates X.
The dependent variable - food consumption equivalent - is winsorized at the 1 % level of the whole sample.
Standard errors in parentheses are clustered at the village level.
*** p<0.01, ** p<0.05, * p<0.1

Table 6: DiD regressions for Food consumption for Shelterbelt Treatment

	Shelterbelt Treatment								
	Total food consumption			Home food consumption			Purchased food consumption		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Period of Interest : 2013 - 2016									
Post x Treat	1,772	4,549	3,920	-119.1	899.2	2.542	1,730	3,333	3,613*
	(3,273)	(3,166)	(3,114)	(1,376)	(1,472)	(1,440)	(2,227)	(2,144)	(2,045)
Observations	2,258	2,258	2,258	2,258	2,258	2,258	2,258	2,258	2,258
R-squared	0.202	0.224	0.229	0.155	0.161	0.164	0.162	0.186	0.189
Placebo Period : 2011 - 2013									
Post x Treat	1,773	1,033	1,609	1,388	467.4	1,578	411.3	607.1	88.29
	(1,556)	(1,729)	(1,633)	(1,022)	(1,100)	(1,075)	(1,144)	(1,371)	(1,201)
Observations	2,379	2,379	2,379	2,379	2,379	2,379	2,379	2,379	2,379
R-squared	0.253	0.255	0.261	0.146	0.155	0.160	0.220	0.222	0.227
Household Controls X_i	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$POST_i$ x X_i	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
PS Reweighting	No	No	Yes	No	No	Yes	No	No	Yes

Difference in difference estimations based on 2011, 2013 and 2016 post harvest LSMS. The household falls into the treatment group if it is less than 20 kilometres far from a shelterbelt project. The weights for IPW are computed from covariates X.
The dependent variable - food consumption equivalent - is winsorized at the 1 % level of the whole sample.
Standard errors in parentheses are clustered at the village level.
*** p<0.01, ** p<0.05, * p<0.1

5 Discussion

The Sub-Saharan African households are particularly vulnerable to growing soil desertification. 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 use socio-economic data and location of the greening activities to explore the impact of the program on children's height-to-age and households' food consumption. 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. Placebo checks and IPW method enrich the empirical framework and control for the identification issues that may occur from the not-random location and implementation of the projects.

The difference-in-difference estimates show a positive and significant impact of proximity to the GGW projects on height-to-age of the treated children. In particular, the children living close to a new community-based orchard enjoys a 14% to 19% increase in their HAZ depending on the specification. This result survives to more a more restrictive definition of control group. Furthermore, we discover that this health improvement mainly occurs through better food access for the surrounding households. The shelterbelt projects are also associated to significant health improvements across all specifications. However, the channels investigation prevents us from concluding that this health improvement stems from a better food access. Given that shelterbelt are rows of trees planted around farmlands to protect them from soil erosion, further research needs to understand whether these new projects eventually enhance crops productivity.

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 in many different ways 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, such as the Zaï. 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.

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A Appendix : Balance Tables

Table A1: Balance Table for Pre-Treatment Year for children in DHS

	2013		
Variable	Control group	Treatment group	Difference
height/age standard deviation	-1.983	-2.253	-0.270***
	(2.056)	(2.000)	(0.055)
number of household members	7.828	7.728	-0.099
	(3.643)	(3.759)	(0.083)
sex of household head	1.041	1.045	0.004
	(0.198)	(0.207)	(0.005)
age of household head	41.237	40.533	-0.704***
	(11.660)	(11.348)	(0.262)
education in single years	1.302	0.752	-0.550***
	(3.493)	(4.418)	(0.084)
1 if respondent is Christian	0.054	0.018	-0.035***
	(0.226)	(0.134)	(0.005)
1 if respondent is Muslim	0.932	0.976	0.044***
	(0.251)	(0.152)	(0.005)
1 if respondent is currently married	0.976	0.987	0.011***
	(0.153)	(0.112)	(0.003)
time to get to water source (minutes)	19.989	21.746	1.757***
	(29.168)	(23.697)	(0.637)
Mother body mass index	2,185.256	2,097.372	-87.885***
	(376.326)	(320.789)	(8.339)
Drought Episodes during 1980-2000	6.183	4.717	-1.466***
	(2.327)	(1.735)	(0.050)
Observations	8,833	2,505	11,338

Treatment group includes all the rural children who are less than 20 km far from any Great Green Wall Project.

Table A2: Balance Table for Pre-Treatment Year for households in LSMS

	2013		
Variable	Control group	Treatment group	Difference
Food consumption per adult	19,919.367	23,387.361	3,467.994
	(70,786.492)	(105838.227)	(4,422.845)
Food consumption per adult	16,921.900	14,384.163	-2,537.737
(winsorized)	(34,824.609)	(18,369.457)	(1,881.429)
Age of the household head	49.993	48.868	-1.125
	(13.846)	(14.087)	(0.800)
Sex of the household head	1.024	1.028	0.004
	(0.152)	(0.165)	(0.009)
Household size	7.176	6.994	-0.182
	(3.244)	(2.972)	(0.184)
Rainfall in wettest quarter	648.421	633.286	-15.135**
	(100.587)	(129.501)	(6.045)
Observations	1,985	360	2,345

Treatment group includes all the rural households who are less than 20 km far from any Great Green Wall Project.

B Appendix: Determinants of the treatment

Table A3: Determinants of the treatment

	(1) Orchard Treatment	(2) Shelterbelt Treatment
Number of household Members	0.0103	-0.0580**
	(0.0210)	(0.0269)
Sex of household head	0.440	0.665
	(0.342)	(0.450)
Age of household head	-0.000291	0.0176***
	(0.00529)	(0.00565)
Education of household head	-0.0189	-0.128*
	(0.0398)	(0.0713)
Christian	-0.109	-1.171
	(0.890)	(1.092)
Muslim	0.952**	1.466**
	(0.471)	(0.711)
Married	0.409	0.260
	(0.344)	(0.592)
Time to water source	0.000422	-0.00922
	(0.00394)	(0.00742)
Drought episodes	-0.285***	-0.150
	(0.0737)	(0.0926)
Mother Body Mass Index	-0.00100***	-0.000340
	(0.000248)	(0.000259)
Observations	11,066	11,066

The outcome is a dummy equal to one if the child received the treatment. The sample is restricted to children from 2013 DHS wave. A logit estimator is used.
Standard errors in parentheses are clustered at the village level.
*** p<0.01, ** p<0.05, * p<0.1

C Appendix: Alternative definition for treatment: All projects

Table A4: DiD regressions for Height to Age for All Projects Treatment

	All projects				
	(1)	(2)	(3)	(4)	(5)
Period of Interest : 2013 - 2018					
Post x Treat	0.295**	0.294**	0.292**	0.356***	0.409***
	(0.126)	(0.126)	(0.127)	(0.122)	(0.126)
Observations	10,896	10,896	10,896	10,896	10,896
R-squared	0.020	0.022	0.032	0.151	0.151
Placebo Period : 2003 - 2013					
Post x Treat	-0.0132	-0.0456	-0.0679	-0.0146	-0.134
	(0.221)	(0.225)	(0.218)	(0.211)	(0.199)
Observations	8,871	8,871	8,871	8,871	8,871
R-squared	0.020	0.021	0.035	0.149	0.149
Individual Controls X_i	Yes	Yes	Yes	Yes	Yes
$POST_i$ x X_i	No	Yes	Yes	Yes	Yes
Birth Month FE	No	No	Yes	No	No
Birth Month x Birth Year FE	No	No	No	Yes	Yes
PS Reweighting	No	No	No	No	Yes

Difference in difference estimations based on 2003, 2013 and 2018 DHS. The child falls into the treatment group if she's less than 20 kilometers far from any type of Great Green Wall project.

Standard errors in parentheses are clustered at the village level.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

D Appendix: Exclusion of children between 20 and 40 KM

Table A5: DiD regressions for Height to Age for Orchard Treatment

	Orchard Treatment				
	(1)	(2)	(3)	(4)	(5)
Period of Interest : 2013 - 2018					
Post x Treat	0.283**	0.279*	0.278*	0.336**	0.381***
	(0.142)	(0.143)	(0.143)	(0.137)	(0.142)
Observations	8,534	8,534	8,534	8,534	8,534
R-squared	0.018	0.020	0.029	0.153	0.152
Placebo Period : 2003 - 2013					
Post x Treat	0.241	0.145	0.0938	0.226	0.143
	(0.250)	(0.252)	(0.242)	(0.241)	(0.231)
Observations	6,779	6,779	6,779	6,779	6,779
R-squared	0.019	0.020	0.033	0.155	0.155
Individual Controls X_i	Yes	Yes	Yes	Yes	Yes
$POST_i$ x X_i	No	Yes	Yes	Yes	Yes
Birth Month FE	No	No	Yes	No	No
Birth Month x Birth Year FE	No	No	No	Yes	Yes
PS Reweighting	No	No	No	No	Yes

Difference in difference estimations based on 2003, 2013 and 2018 DHS. The child falls into the treatment group if she's less than 20 kilometers far from an orchard project. The control group is restricted to children located at least 40 kilometers far from an orchard project.
Standard errors in parentheses are clustered at the village level.
*** p<0.01, ** p<0.05, * p<0.1

Table A6: DiD regressions for Height to Age for Shelterbelt Treatment

	Shelterbelt Treatment				
	(1)	(2)	(3)	(4)	(5)
Period of Interest : 2013 - 2018					
Post x Treat	0.496**	0.493**	0.509**	0.582**	0.453*
	(0.244)	(0.245)	(0.243)	(0.235)	(0.265)
Observations	9,245	9,245	9,245	9,245	9,245
R-squared	0.019	0.021	0.031	0.157	0.158
Placebo Period : 2003 - 2013					
Post x Treat	0.274	0.319	0.229	0.294	0.310
	(0.448)	(0.468)	(0.474)	(0.379)	(0.430)
Observations	7,465	7,465	7,465	7,465	7,465
R-squared	0.018	0.020	0.034	0.154	0.155
Individual Controls X_i	Yes	Yes	Yes	Yes	Yes
$POST_i$ x X_i	No	Yes	Yes	Yes	Yes
Birth Month FE	No	No	Yes	No	No
Birth Month x Birth Year FE	No	No	No	Yes	Yes
PS Reweighting	No	No	No	No	Yes

Difference in difference estimations based on 2003, 2013 and 2018 DHS. The child falls into the treatment group if she's less than 20 kilometers far from a shelterbelt project. The control group is restricted to children located at least 40 kilometers far from an shelterbelt project.

Standard errors in parentheses are clustered at the village level.

*** p<0.01, ** p<0.05, * p<0.1

E Appendix : Food Consumption per Adult Equivalent is Not Winsorized

Table A7: DiD regressions for Food consumption for Orchard Treatment

	Orchard Treatment								
	Total food consumption			Home food consumption			Purchased food consumption		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Period of Interest : 2013 - 2016									
Post x Treat	11,020**	11,233**	11,674**	1,477	1,534	1,415	9,543**	9,699**	10,259**
	(5,396)	(5,193)	(5,261)	(1,150)	(1,149)	(1,141)	(4,766)	(4,646)	(4,743)
Observations	2,258	2,258	2,258	2,258	2,258	2,258	2,258	2,258	2,258
R-squared	0.099	0.121	0.121	0.133	0.137	0.138	0.072	0.096	0.096
Placebo Period : 2011 - 2013									
Post x Treat	-6,236*	-6,638*	-6,948**	289.2	130.7	165.7	-6,525**	-6,769**	-7,113**
	(3,475)	(3,464)	(3,440)	(902.3)	(849.8)	(891.4)	(3,147)	(3,226)	(3,188)
Observations	2,379	2,379	2,379	2,379	2,379	2,379	2,379	2,379	2,379
R-squared	0.154	0.156	0.157	0.124	0.132	0.133	0.129	0.131	0.131
Household Controls X_i	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$POST_i$ x X_i	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
PS Reweighting	No	No	Yes	No	No	Yes	No	No	Yes

Difference in difference estimations based on 2011, 2013 and 2016 post-harvest LSMS. The household falls into the treatment group if it is less than 20 kilometres far from an orchard project. The weights for IPW are computed from covariates X.
The dependent variable, food consumption equivalent, is not winsorized anymore.
Standard errors in parentheses are clustered at the village level.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A8: DiD regressions for Food consumption for Shelterbelt Treatment

	Shelterbelt Treatment								
	Total food consumption			Home food consumption			Purchased food consumption		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Period of Interest : 2013 - 2016									
Post x Treat	5,661	9,002	8,262	44.91	1,017	141.0	5,616	7,985	8,121*
	(6,138)	(5,968)	(5,727)	(1,391)	(1,481)	(1,443)	(5,166)	(4,995)	(4,718)
Observations	2,258	2,258	2,258	2,258	2,258	2,258	2,258	2,258	2,258
R-squared	0.098	0.120	0.124	0.132	0.137	0.140	0.071	0.095	0.097
Placebo Period : 2011 - 2013									
Post x Treat	-118.1	-880.7	-226.3	1,209	291.6	1,391	-1,328	-1,172	-1,617
	(2,142)	(2,248)	(2,021)	(1,035)	(1,105)	(1,072)	(1,684)	(1,881)	(1,600)
Observations	2,379	2,379	2,379	2,379	2,379	2,379	2,379	2,379	2,379
R-squared	0.153	0.155	0.162	0.126	0.133	0.139	0.128	0.130	0.135
Household Controls X_i	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$POST_i$ x X_i	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
PS Reweighting	No	No	Yes	No	No	Yes	No	No	Yes

Difference in difference estimations based on 2011, 2013 and 2016 post harvest LSMS. The household falls into the treatment group if it is less than 20 kilometres far from a shelterbelt project. The weights for IPW are computed from covariates X.

The dependent variable, food consumption equivalent, is not winsorized anymore.

Standard errors in parentheses are clustered at the village level.

*** p<0.01, ** p<0.05, * p<0.1

F Appendix: Introducing 2008 DHS

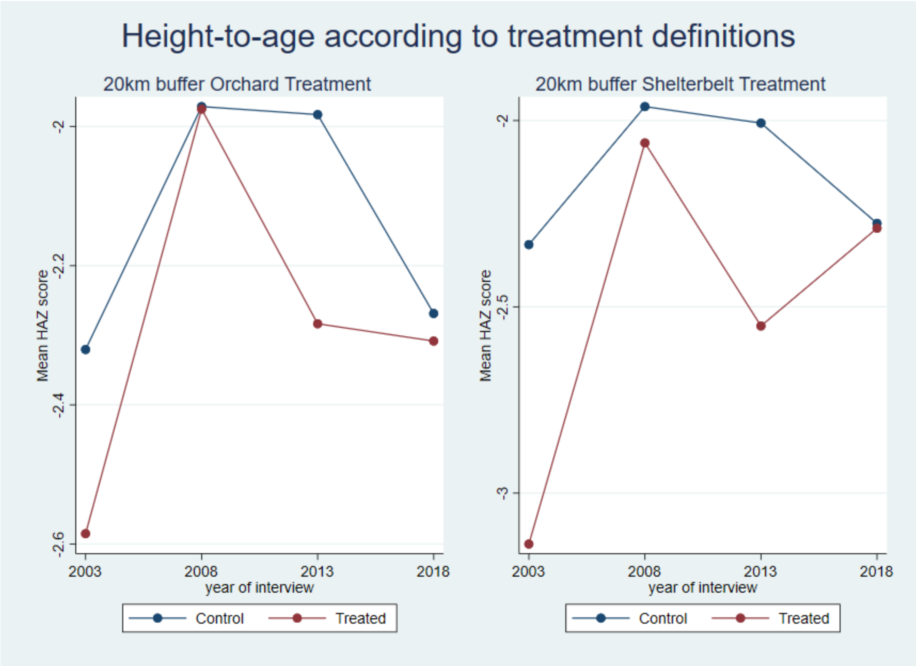

Figure A1: The evolution of height-to-age under two treatment definitions

Table A9: DiD regressions on height-to-age for Orchard Treatment

	Orchard Treatment				
	(1)	(2)	(3)	(4)	(5)
Placebo Period : 2008 - 2013					
Post x Treat	-0.332**	-0.345**	-0.349**	-0.287**	-0.376***
	(0.139)	(0.139)	(0.138)	(0.134)	(0.139)
Observations	13,632	13,632	13,632	13,632	13,632
R-squared	0.011	0.012	0.019	0.134	0.135
Individual Controls X_i	Yes	Yes	Yes	Yes	Yes
$POST_i$ x X_i	No	Yes	Yes	Yes	Yes
Birth Month FE	No	No	Yes	No	No
Birth Month x Birth Year FE	No	No	No	Yes	Yes
PS Reweighting	No	No	No	No	Yes

Difference-in-difference estimations based on 2008 and 2013 DHS. The child falls into the treatment group if she's less than 20 kilometers far from an orchard project.
Standard errors in parentheses are clustered at the village level.
*** p<0.01, ** p<0.05, * p<0.1

Table A10: DiD regressions on height-to-age for Shelterbelt Treatment

	Shelterbelt Treatment				
	(1)	(2)	(3)	(4)	(5)
Placebo Period : 2008 - 2013					
Post x Treat	-0.490**	-0.467**	-0.492**	-0.490**	-0.540***
	(0.237)	(0.236)	(0.237)	(0.240)	(0.256)
Observations	13,632	13,632	13,632	13,632	13,632
R-squared	0.011	0.012	0.019	0.134	0.133
Individual Controls X_i	Yes	Yes	Yes	Yes	Yes
$POST_i$ x X_i	No	Yes	Yes	Yes	Yes
Birth Month FE	No	No	Yes	No	No
Birth Month x Birth Year FE	No	No	No	Yes	Yes
PS Reweighting	No	No	No	No	Yes

Difference-in-difference estimations based on 2008 and 2013 DHS. The child falls into the treatment group if she's less than 20 kilometers far from a shelterbelt project.
Standard errors in parentheses are clustered at the village level.
*** p<0.01, ** p<0.05, * p<0.1