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Victor Cordonnier

Katia Alejandra Covarrubias

Ana Paula de la O Campos

Food and Agriculture Organization of the United Nations

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Abstract

This paper assesses the food security impacts of widespread agricultural interventions, aiming at increasing agricultural yields, and explores the role played by adjustments in rural households' livelihood strategies in mediating those impacts. Our empirical strategy combines project and remote-sensing data with a household panel survey and exploits the timing and geographic variation in the roll-out of interventions implemented from 2011 to 2016 by the Ethiopian Agricultural Transformation Agency (ATA), recently renamed as Agricultural Transformation Institute (ATI).

Results show that agricultural interventions are effectively associated with higher agricultural yields, better food security outcomes and adjustments in livelihood strategies. However, when exploring the role of livelihood strategies through a Causal Mediation Analysis, we show that livelihood adjustments do not seem to play any mediating role in food security impacts. Heterogeneity analysis suggests that the absence of a mediating role stems from agricultural interventions affecting different types of households differently: the most vulnerable households primarily benefited through food security improvements while more-endowed households adjusted their livelihood strategies.

Keywords: Ethiopia, agricultural transformation, agricultural interventions, food security, rural households; livelihood strategies, impact evaluation, propensity score, two-way fixed effects, causal mediation analysis

JEL codes: I3, I38, J24, J43, O13, O22, O55, Q12.

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1 Introduction

As in most sub-Saharan African countries, agriculture in Ethiopia is dominated by smallholder farmers primarily relying on agricultural production for household subsistence. However, declining farm size due to rising population pressure and repeated agricultural shocks have placed Ethiopian farmers in a situation of high vulnerability, making food insecurity a persistent challenge in Ethiopia. Agricultural interventions that aim at improving agricultural productivity by removing bottlenecks in terms of access and use of modern agricultural practices are expected to lead to higher food security primarily by providing farm households with more food produced for their own-consumption or greater liquidity to purchase food, through commercialization of agricultural products. Besides this direct effect, agricultural productivity gains can also have an effect on food security through the indirect effect of adjustment in rural households' livelihood strategies. Indeed, agricultural productivity gains can allow rural households to engage in more food secure livelihood strategies by providing them the possibility to reallocate labour, offering access to additional sources of income, and in turn a better capacity to smooth consumption and deal with shocks (Webb and Reardon, 1992; Reardon, Delgado and Matlon, 1992; Barrett, Reardon and Webb, 2001). While numerous studies have evaluated the food security impacts of productivity-improving agricultural interventions (see Bizikova *et al.* [2020] for a recent overview of these studies), no study that we are aware of, has empirically tested the role that household livelihood adjustments have in the pathway from agricultural productivity gains to food security.

This paper assesses the food security impacts of widespread agricultural interventions, aiming at promoting agricultural productivity, and explore the extent to which those impacts are mediated by adjustments in rural households' livelihood strategies. Combining project and remote sensing data with a household panel survey, our empirical strategy exploits the spatial and temporal variation in the roll-out of interventions implemented by the Agricultural Transformation Agency (ATA)[1] of Ethiopia from 2011 to 2016. This paper builds on the findings of FAO (2020), which assessed the ten-year impacts of the ATA in an *ex post* framework, finding significant yield improvements as well as increased use of modern inputs. At the level of the macroeconomy, computable general equilibrium (CGE) modelling by FAO (2020) also documented various local economy effects, notably in terms of job creation in different sectors of the economy.

Through a doubly robust analysis, we demonstrate that by increasing agricultural yields ATA's agricultural interventions until 2016 effectively led to higher food security outcomes and promoted some adjustments in rural households' livelihood strategies. However, we do not find any evidence that those adjustments were a channel through which food security improvements emerged. Instead, for the 2011 to 2016 period, ATA's impact on food security seems fully driven by the production expansion of ATA's agricultural interventions in Ethiopia's agricultural system. In addition, we find evidence that rural households that benefited from food security gains differ from those that adjusted their livelihood strategies. In particular, food security impacts appear to be concentrated among most vulnerable households while adjustments in livelihood strategies seem concentrated among more endowed households. Finally, while we do not find evidence of positive spillover effects, we do find suggestive evidence of strong positive agglomeration effects as results show that only treated districts adjacent to other treated districts

[1] As of 2022, the agency has been renamed the Agricultural Transformation Institute (ATI).

experienced an increase in agricultural yields. Overall, we conclude that ATA's agricultural interventions were successful in increasing farmers' welfare and food security, and facilitated transitions towards the non-agricultural sector, thereby contributing to the process of structural transformation in Ethiopia.

The focus of this paper seeks to address the policy priorities raised in the Growth and Transformation Plans of the Government of Ethiopia, which aim at accelerating agricultural transformation and achieving industrialization and middle-income status. This paper informs those policy priorities in two ways. First, by evaluating the food security outcomes of ATA's agricultural interventions, our results contribute to assessing whether the process of agricultural transformation has generated positive externalities in terms of food and nutrition security. Furthermore, our mediation analysis explores whether agricultural development indeed promotes rural households' participation in livelihood strategies outside of the agricultural sector. Such a process has been observed in other developed and emerging countries, and is identified as a fundamental aspect of the structural transformation process of a country's economy.

The rest of the paper is structured as follows. Section 2 provides background on agriculture, food security and livelihood strategies in Ethiopia and on the agricultural investments implemented by the Agricultural Transformation Agency of Ethiopia. Section 3 presents the conceptual framework underlying the empirical analysis. Section 4 describes the methodology in terms of data, indicators and empirical strategy. Section 5 presents the main results and Section 6 digs into the pathways. Section 7 discusses policy implications and concludes.

2 Background

2.1 Agriculture, food security and livelihood strategies in Ethiopia

Agriculture is at the forefront of the Ethiopia's economy with more than two-thirds of the active population working in the agricultural sector (World Bank, 2019a). Agricultural production is dominated by smallholder family farmers with relatively low access to modern agricultural practices as fewer than 25 percent of farmers use improved seeds, slightly more than 35 percent of them use agrochemicals, about 55 percent use inorganic fertilizer and less than 10 percent have irrigated parcels (Covarrubias, de la O Campos and Cordonnier, 2021). While the majority of farmers do sell some of their production, agriculture is primarily for subsistence as on average, farmers sell less than 20 percent of their output (Covarrubias, de la O Campos and Cordonnier, 2021). The fact that most agricultural production is consumed by farmers highlights how important agriculture is for rural households' food security. However, despite demonstrated growth in terms of agricultural yields and some improvements in terms of poverty reduction, high levels of food insecurity persist in Ethiopia. Indeed, more than half of the population suffers from moderate or severe food insecurity, close to 25 percent of reproductive age women suffer from anaemia and more than 35 percent of children under five are stunted (World Bank, 2019b, 2019c, 2019d). Food insecurity in Ethiopia is likely the result of a combination of both structural and conjunctural factors that constrain agricultural production and prevent meeting food requirements. Those factors include small and decreasing farm size (due to increasing population pressure), low and declining soil fertility (due to intensive cultivation) and repeated agricultural shocks (such as droughts or locust invasion) (Dorosh and Minten, 2020). Food-insecure livelihood strategies may also be one of these factors as on-farm specialization likely make rural households more vulnerable to agricultural and economic shocks (Devereux, 2000). Ethiopia is indeed characterized by a predominance of on-farm specialization as about 60 percent of rural households are engaged only in on-farm activities, while less than 30 percent operate a diversified portfolio and primarily by combining on-farm activities with temporary labour (Covarrubias, de la O Campos and Cordonnier, 2021). Participation in off-farm activities is more common among poorer households, suggesting the relative dominance of off-farm participation as a consumption-smoothing or risk-response strategy, rather than one consolidating sustained improvement in living standards (Bachewe *et al.*, 2020; Barrett, Reardon and Webb, 2001; Ellis, 2000).

2.2 The Agricultural Transformation Agency of Ethiopia

The Ethiopian Agricultural Transformation Agency was created in December 2010 with the objective of transforming Ethiopian agriculture and improving the livelihoods of smallholder farmers through the enhancement of efficiency in the delivery of services and in the introduction of innovations to the agricultural sector (ATA, 2021). The transformation agenda seeks to modernize the agricultural sector, focusing on areas that will improve the productivity, sustainability, and competitiveness of the sector (PDC, 2021). In that context, ATA has supported numerous targeted investments in agriculture since 2012 with interventions to improve input supply, production, capacity building, research, aggregation and storage, value addition and extension support, prioritizing specific crop value chains, including malt barley, maize, wheat and teff, among others (ATA, 2021). Between 2011 and 2016, the period of interest in this paper, ATA rolled out eight interventions and piloted its flagship Agricultural

Commercialization Clusters (ACC) Initiative. By 2016, a total of 296 districts (named woredas in Ethiopia) had been targeted by one or more agricultural interventions supported by ATA. The three major projects implemented by ATA between 2011 and 2016 are the Direct Seed Marketing (DSM) programme, which improved market linkages between seed producers and their users, the Input Voucher System (IVS) project, which sought to relax liquidity constraints to fertilizer and improved seed access, and the ACC as a cross-cutting initiative, addressing all dimensions of agricultural system bottlenecks. By 2016, 90 percent of treated districts were targeted by at least one of these three projects. With the objective of maximizing returns to investments, ATA's agricultural interventions typically target areas with high agricultural potential and market access (ATA, 2017), while in their implementation they seek to adapt their approach to the specific needs of female farmers as part of efforts to disproportionately target women.

Recent studies have shown that ATA's agricultural interventions effectively contributed to the modernization of agriculture in Ethiopia. Through a randomized control trial setting, Abate *et al.* (2018) shows that ATA's Wheat Initiative promoted the adoption of fertilizer and certified seeds and increased yields by about 14 percent. Using cross-sectional data in a microlevel analysis with a propensity score approach, FAO (2020) finds that ATA's agricultural interventions implemented from 2012 to 2019 are associated with a higher use of modern agricultural inputs (improved seeds, agrochemicals, fertilizer). Exploiting the progressive expansion of the DSM programme in a difference-in-difference framework, Mekonnen *et al.* (2021) provides evidence that the intervention led to improvements in seed availability for Ethiopia's major cereals – maize, wheat and teff – as well as an increase in maize yields by about 26 percent and in the share of maize harvest sold by 5 percent (but no significant effects for wheat and teff, neither for yields nor for commercialization). Whereas none of these studies have assessed secondary effects on food security or non-agricultural livelihood strategies of those ATA's agricultural interventions, FAO (2020) did demonstrate through a CGE model that the stock of ATA's agricultural interventions until 2019 contributed to an 11-percentage point reduction in the poverty rate, while also simulating growth in the non-agricultural economy, through demand for non-food products and job creation in non-farm sectors.

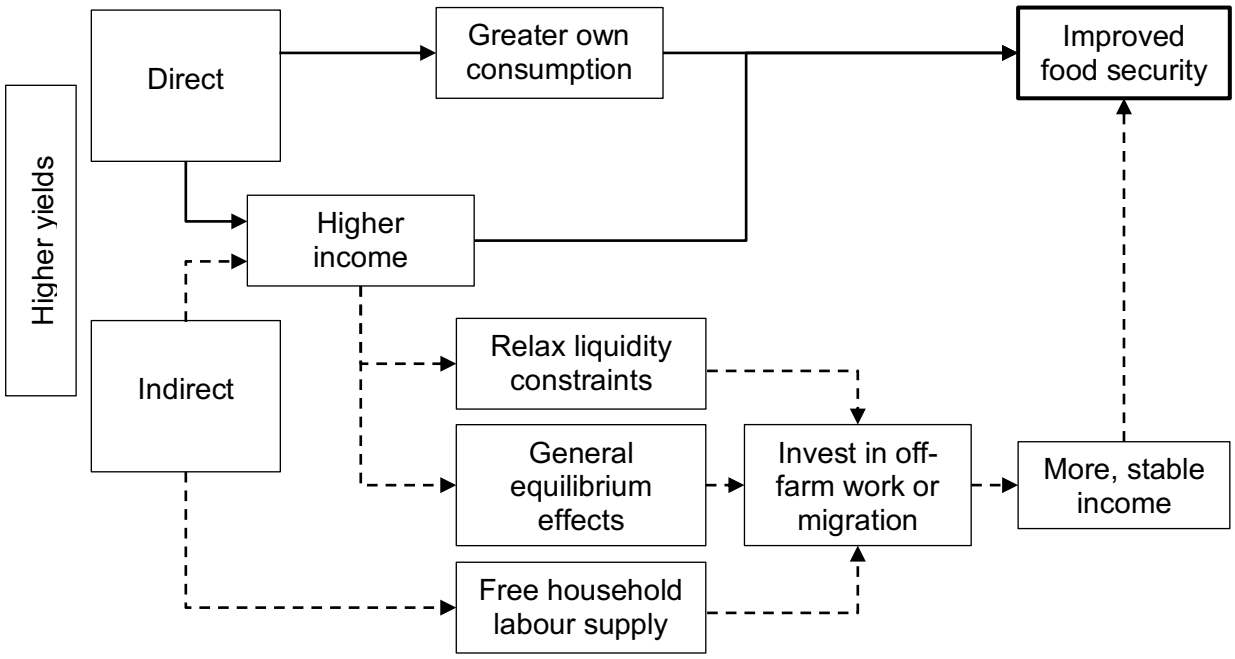
3 Conceptual framework

The primary objective of ATA's interventions is to increase agricultural yields. Those gains are expected to translate into higher food security through both direct and indirect channels. Those gains may *directly* affect food security, through the simple fact that higher yields can translate into more food produced for self-consumption or into higher income to purchase food. Studies from various contexts show that productivity improving agricultural interventions are associated with higher consumption (Awotide *et al.*, 2013) and better food security outcomes (Salazar *et al.*, 2015; Pan, Smith and Sulaiman, 2018).

Yields gains associated with those agricultural interventions may also *indirectly* affect food security through a labour reallocation toward more food secure livelihood strategies. First, productivity gains in on-farm activities may provide rural households with free labour supply to engage in high-returns off-farm activities or migration (Gollin, Parente and Rogerson, 2002; Bustos, Caprettini and Ponticelli, 2016). Second, higher yields can translate into higher income and allow rural household to relax the liquidity constraints to engage in off-farm activities or migration (Haggblade, Hazell and Reardon, 2010). Last, on a general equilibrium perspective, higher income generated from productivity gains in on-farm activities may translate into higher demand for non-food consumption goods and boost labour opportunities in the off-farm sector (Foster and Rosenzweig, 2007; Emerick, 2018). This labour reallocation toward high-returns off-farm activities and migration could then provide rural households with additional and more stable sources of income (Asfaw *et al.*, 2019) in turn could contribute to improved household food security (Zereyesus *et al.*, 2017; Block and Webb, 2001; Bezu, Barrett and Holden, 2012; Babatunde and Qaim, 2010; Owusu, Abdulai and Adbul-Rahman, 2011; Tsiboe, Zereyesus and Osei, 2016; Rahman and Mishra, 2020).

Figure 1 summarizes the direct and indirect channels from higher yields to higher food security.

Figure 1. Overview of the direct and indirect channels



Source: Authors' own elaboration.

4 Data and methods

4.1 Data

Our analysis combines three major sources of data. The first source is project data on the progressive roll-out of agricultural interventions by Ethiopia's ATA. The second source of data, and main source to monitor food security and livelihood strategies among rural households is the Ethiopia Socio-economic Survey (ESS). The survey, implemented by the Central Statistical Agency (CSA) in collaboration with the World Bank, is a nationally representative rural panel household survey implemented in 2011/12,[2] 2013/14 and 2015/16[3] that collected information at the individual, household, agricultural holding and community levels, with dedicated modules on economic activity participation, income earned, agricultural activities, and food security, among others (CSA, 2012, 2014, 2016). However, ESS data lack consistent and robust measure of agricultural yields across the full study period due to problems with implementation of the agricultural questionnaire during the first wave (CSA and World Bank, 2012). To overcome this issue, our third source of data is satellite imagery from the Moderate Resolution Imaging Spectroradiometer (MODIS) that provides frequent data on surface reflectance at the 250 metres resolution since 2000 (Didan, 2015), allowing us to proxy changes in agricultural yields with changes in vegetation over time.[4]

Our analysis also relies on additional sources of data. First, to construct a valid counterfactual based on district level data, observed for all districts in Ethiopia prior to the implementation of ATA's agricultural interventions, we use data from the Global Agro-Ecological Zones (GAEZ) portal (FAO and IIASA, 2021), geospatial data on market accessibility in sub-Saharan Africa (HarvestChoice and IFPRI, 2018), a machine-learning-based Asset Wealth Index (Atlas AI, 2021) and the Integrated Public Use Microdata Series (IPUMS) census extract of the 2007 Population and Housing Census of Ethiopia (Minnesota Population Center, 2020). Second, to control for time-varying factors that may be both correlated with the roll-out of ATA's interventions and outcomes of interest we use rainfall data from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), that provide daily precipitation at the 0.05° resolution (about 55km) (Funk *et al.*, 2014), and population data from WorldPop, which provides the estimated number of people living in grid cells of about 100x100 metres (WorldPop, 2021).

4.2 Indicators

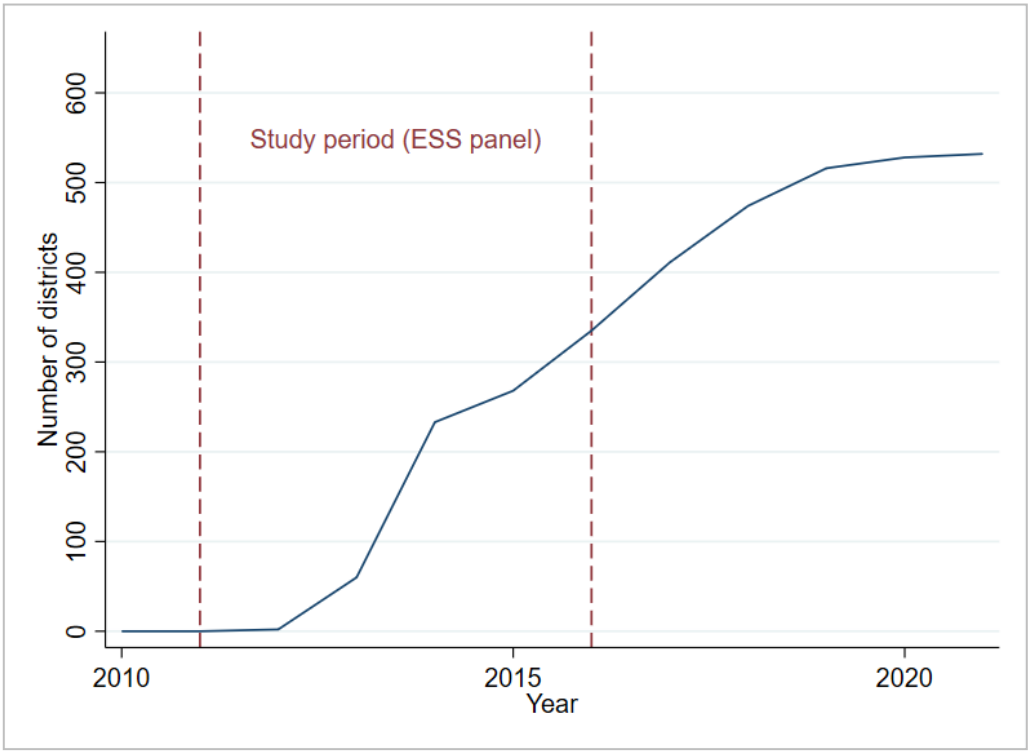
To estimate the impact of ATA's agricultural interventions we construct a treatment variable to exposure to agricultural interventions implemented by ATA over the 2012 to 2016 period. Since ATA typically targeted agricultural interventions at the district level, a district is considered as treated when any of ATA's agricultural interventions started to be implemented in its territory.

[2] The 2011/12 wave of the survey was instead called the Ethiopia Rural Socio-economic Survey.

[3] The survey was implemented again in 2018/2019 but with a new sample of households, preventing us to include this last wave in the panel analysis.

[4] An alternative would be to use Landsat data at 30 metres resolution (USGS, 2021). However, the drawback of such high-resolution data is it contains many missing values for the periods of interest, primarily due to cloud cover.

Figure 2. Number of treated districts over the study period



Source: Authors' own elaboration using ATA. 2020. *District-level project coverage data*. Personal communication.

To provide evidence that agricultural interventions promoted agricultural yields, we explore the effect of ATA's interventions on the normalized difference vegetation index (NDVI). NDVI is the most used index of vegetation, and its construction is based on surface reflectance.[5] NDVI measures the degree of "greenness" of an area and varies between -1 to 1, with higher values corresponding to areas with more or denser vegetation. NDVI has been widely used in the literature as a proxy for agricultural yields (Sultana *et al.*, 2014; Moriondo, Maselli and Bindi, 2017; Panek and Gozdowski, 2021; Salazar *et al.*, 2021; Gazeaud and Stephane, 2022) and some recent evidence suggest that satellite-based yield measures perform as well (Burke and Lobell, 2017) or even better (Lobell *et al.*, 2020) than most common ground-based measures such as farmer-reporting or sub-plot crop cutting. We compute NDVI at the district level for each year from 2011 to 2016. Since the objective of our analysis is to specifically capture changes in agricultural yields, we impose spatial and temporal constraints when computing NDVI at the district level, adopting a similar approach than Gazeaud and Stephane (2022). In terms of spatial constraint, we focus on areas covered by cropland based on the land cover maps provided by the European Space Agency (ESA) in context of the Climate Change Initiative (ESA, 2017). On the temporal dimension, we focus on the *Meher* season, Ethiopia's main growing period, running from June until December, with harvest starting from October or November depending on the crops. To capture the peak of the growing period, we compute the NDVI for the months from June to October.[6] Following Gazeaud and Stephane (2022) we use the 2013/2014 and

[5] The formula is $\mathrm{NDVI} = \frac{\mathrm{NIR}-\mathrm{Red}}{\mathrm{NIR}+\mathrm{Red}}$ where Red and NIR stand for the red and near-infrared surface reflectance, respectively.

[6] Since climatic conditions across the country may stagger the onset of the *Meher* harvest, we report main results for four additional reference periods extending from June to August to June to December.

2015/2016 ESS waves to show that our NDVI indicator is significantly correlated with the ground-based measure of agricultural yields and that an increase in NDVI by 0.01 units is associated with an increase in cereal yields of about 5.6 percent (Table A2).

The primary household-level outcome assessed by our analysis is food security. To capture the multidimensionality of food security, we consider various indicators commonly used in the literature. First, we consider an indicator for having experienced any food gap (insufficient access to food) in the 12 months prior to the survey and the number of months this event occurred (conditional on having experienced a food gap). Second, we capture dietary diversity through the Household Dietary Diversity (HDD) score and the Food Consumption Score (FCS).[7] Last, we consider the log of total food consumption in adult equivalent units.[8]

Our analysis aims to explore the potential role played by adjustments in livelihood strategies in the pathway from agricultural production gains to food security. We consider livelihood strategies in terms of both labour and migration strategies. We construct a typology of labour strategies to distinguish households with no labour activities, those that are specialized in on-farm activities, and those that engaged in off-farm activities. To reflect the duality between participation into low- versus high-return off-farm activities, we distinguish between participation in survival-led versus opportunity-led off-farm activities. The former represents participation in agricultural wage employment, temporary jobs and casual labour. The latter instead captures participation into non-farm self-employment and/or non-agricultural wage employment. We analyse separately livelihood strategies that rely on migration of household members, because the ESS data does not enable a reliable classification into survival versus opportunity-led migration. Migration captures households having at least one member away for more than four months, having at least one member who left since the previous wave or having at least one member who migrated in response to a shock.

4.3 Empirical strategy

4.3.1 Constructing the counterfactual through propensity score estimation

The objective of this paper is to estimate the impact of ATA's agricultural interventions on agricultural yields, food security and livelihood strategies. Because assignment of ATA's agricultural interventions is not random, we rely on inverse probability weighting, drawing on ATA's targeting criteria (ATA, 2017) to construct a valid counterfactual and provide robust estimates. Propensity score methods are considered the best practice to estimate the causal effect of programmes or policies in a context of non-random assignment (Imbens and Wooldridge, 2009), hence their application in this context.

In practice, we rely on administrative and spatial pre-treatment data to estimate the probability of assignment to a treatment district, conditional on observed covariates measured before the treatment (Rosenbaum and Rubin, 1983; Austin, 2011). The estimated propensity scores are then used to calculate balancing scores to construct a valid counterfactual from untreated

[7] The Household Dietary Diversity score captures the number of food groups consumed in the previous seven days, while the Food Consumption Score adds weights to these food groups reflecting the nutrient density of each food group.

[8] ESS data provide annual food consumption estimates constructed from the consumption module, which reports household food intake from all potential sources over the previous seven days, deflated through spatial price indexes. Total food consumption is expressed in real terms.

observations. Applying this inverse probability weighting method to all regressions provides a doubly robust estimate of the average treatment effect (Morgan and Winship, 2015).

Since the targeting of ATA's agricultural interventions typically consists in selecting districts based on their agricultural potential, access to markets, and local economic conditions (ATA, 2017),[9] our estimation of propensity scores is based on indicators that reflect the above criterion, sourced from administrative and spatial data collected before the onset of ATA's agricultural interventions. Agricultural potential is captured by the length of the growing period (i.e. the total number of days where soil moisture is suitable for agriculture), the potential yields of maize (to capture potential cereals yields) and the potential yields of banana (to capture potential yields of horticulture crops).[10] Market access is captured by the average number of hours to a market based in a locality of at least 20 000 inhabitants. Local economic conditions are captured by the share of adults in non-farm wage employment as primary occupation and an Asset Wealth Index constructed from Demographic and Health Surveys (DHS) variables and satellite imagery on land cover, elevation and night-time luminosity.

The propensity score estimation is based on the full set of Ethiopian districts, and considering all areas in which ATA held operations, which considerably increases its statistical power.[11] The propensity scores can then be utilized to estimate treatment effects on NDVI for the entire Ethiopian territory, as well as for the subset of districts covered by the ESS when estimating impacts on food security and livelihood strategies.

Table 1 reports the means of pre-treatment variables in the treated and control districts before and after adjusting through inverse probability weighting, demonstrating that the adjustment effectively manages to attain balance across all pre-treatment covariates.

[9] In the design of ATA's agricultural interventions, specific attention is dedicated to women and youth. However, those dimensions do not serve to target the districts in which interventions are implemented.

[10] Potential yields are estimated by GAEZ over the 1981-2010 period through an eco-physiological model that accounts for crop suitability, soil characteristics and climate conditions under different scenarios of access to water and input use. To reflect the characteristics of Ethiopian agriculture, we considered agroclimatic potential yields under the scenario of rain-fed agriculture and low input use.

[11] The main drawback of this strategy is that it cannot account for the potential non-randomness in the progressive implementation of ATA's agricultural interventions. To further control for time-varying factors that could be correlated with this sequential roll-out, we control for rainfall anomaly when estimating the treatment effect.

Table 1. Pre-treatment characteristics

	Before adjustment			After adjustment		
	Control	Treated	Significant	Control	Treated	Significant
Agricultural potential						
Length of the growing period	208.60	225.41	***	222.12	225.28	
Potential yields of maize	2.37	2.68	***	2.60	2.63	
Potential yields of banana	1.50	1.18	***	1.25	1.33	
Market access						
Average time to markets	4.31	2.87	***	3.34	3.41	
Squared average time to market	25.40	10.93	***	16.15	16.68	
Local economy conditions						
Adults in non-farm wage employment	2.96	3.79	***	4.06	3.62	
Asset wealth index	-0.62	-0.60	***	-0.60	-0.61	
Squared asset wealth index	0.39	0.37	***	0.38	0.38	
Districts	306	327		306	327	

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Addis Ababa region excluded. Length of the growing period is expressed in days. Potential yields of maize and banana are expressed in kilograms of dry weight by hectare. Average time to market is defined in terms of hours to market based in a locality of at least 20 000 inhabitants. Adults in non-farm wage employment is expressed in percentage. The Asset Wealth Index is centred around 0.

Source: Authors' own elaboration.

4.3.2 Estimating the impact on agricultural yields

To estimate the effect of ATA's interventions on agricultural yields we exploit the timing and geographic variation in the implementation of ATA's agricultural interventions. In a district-level difference-in-difference (DD) framework, our strategy consists in comparing the changes in NDVI for districts exposed to ATA's agricultural interventions with the changes in NDVI for districts not exposed to ATA's agricultural interventions.[12,13] This strategy allows us to control for both time-invariant unobserved heterogeneity across districts and time-specific attributes that may affect simultaneously the treatment assignment and outcomes.[14]

[12] The key identifying assumption underlying the validity of the DD approach is the parallel trends assumption, which expresses that treatment and control areas would have followed similar pathways in the absence of any ATA agricultural intervention. We take advantage of the fact that the MODIS NDVI series start from 2000 to construct event study graphs and validate the parallel trends assumption.

[13] Impact evaluation methods also rely on the stable unit treatment value assumption (SUTVA) that requires that the potential outcome of one unit should not be affected by the treatment assignment of other units. We evidence the credibility of SUTVA by showing that the treatment effect for NDVI while excluding control districts adjacent to treated districts is similar to the overall treatment effect.

[14] The impact evaluation literature has recently highlighted that two-way fixed effects (TWFE) models may generate biased estimates in contexts of variation in treatment timing and heterogeneity in treatment effects over time (Athey and Imbens, 2006; Baker, Larcker and Wang, 2021; Borusyak and Jaravel, 2017; Callaway and Sant'Anna, 2021; De Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2020). We thus additionally provide ATT estimates obtained from the *DiD with multiple periods estimator* proposed by Callaway and Sant'Anna, 2021 and show that results are consistent.

$$NDVI_{dt} = \alpha + \beta T_{dt} + \gamma_d + \gamma_t + \delta X_{dt} + \varepsilon_{dt} \quad (1)$$

We estimate equation (1) for which $NDVI_{dt}$ is a measure of NDVI for district d at time t; T_{dt} is the treatment variable equal to 1 if any ATA intervention was implemented in district d at time t. γ_d and γ_t are district and time fixed effects, respectively. To control for confounding factors that may be correlated with both treatment assignments and changes in outcomes, time-varying districts characteristics are captured by X_{dt}. Those covariates include rainfall anomaly (discrepancy between actual rainfall and long-term mean rainfall) and total population, measured at the district level. For rainfall measures, we apply the same methodology as for NDVI and consider the months of the main growing period.

4.3.3 Estimating the impact on food security and livelihood strategies

We estimate the effect of ATA's interventions on food security and livelihood strategies in a household-level DD framework. We thus compares the changes in outcomes for rural households living in districts exposed to ATA's agricultural interventions with the changes in outcomes for rural households living in districts not exposed to ATA's agricultural interventions.[15] This strategy allows us to control for both time-invariant unobserved heterogeneity across households (such as household skill level for its chosen livelihood strategy, or social norms that govern its preference set) and time-specific observable and unobservable attributes (such as national level policies or widespread climatic shock) that may affect simultaneously the treatment assignment and outcomes.[16]

$$Y_{idt} = \alpha_1 + \beta_1 T_{dt} + \gamma_i + \gamma_t + \delta_1 X_{idt} + \varepsilon_{1_{idt}} \quad (2)$$

We implement this DD strategy by estimating equation (2), for which Y_{idt} is an outcome of interest for household i, living in district d and measured at time t; T_{dt} equals 1 if any ATA agricultural intervention was implemented in district d at time t; and γ_i and γ_t terms are the aforementioned household and time fixed effects. To control for confounding factors that may affect both treatment assignment and changes in outcomes, time-varying household characteristics are captured by X_{idt}. These variables include household head characteristics, household demographics and education indicators, household wealth and credit access.[17] X_{idt} also includes community-level covariates to account for local prices, remoteness, access to markets and local services such as health posts, financial institutions, cooperatives as well as local participation in the Productive Safety Nets Programme. Last, we control for rainfall

[15] Despite the number of pre-treatment periods available from the ESS data is limited to two, we still construct event study graphs and show that the parallel trends assumption holds for most household-level outcomes of interest. We only find evidence of pre-trends for on-farm specialization and survival-led off-farm, which arguably reflects that participation in low-return off-farm activities is likely the margin on which rural households adjust in the short-term when faced with shocks.

[16] As for NDVI, we provide ATT estimates obtained from the *DiD with multiple periods estimator* proposed by Callaway and Sant'Anna, 2021 and show that results are consistent for most household-level outcomes of interest. Only for on-farm specialization, the ATT estimate differs from the TWFE estimate, which likely reflects the existence of pre-trends for this outcome.

[17] Access to credit is potentially an endogenous variable if it affects simultaneously the treatment and the outcome. In our context, access to credit is potentially endogenous to the main outcome of interest as food insecure households may need to borrow money for consumption purposes. However, since credit access is measured at the household level, it is unlikely endogenous to treatment as assignment to ATA's interventions is defined at the district level. We substantiate our hypothesis by testing the relationship with treatment and find it is not significant (p=0.236).

anomaly for the months of the main growing period (June to October). To account for spatial correlation across households in a same district, and because ATA treatment assignment is correlated across households in a same district, standard errors are clustered at the district level. The average treatment effect, obtained from equation (2), is β_1.

4.3.4 Exploring the mediating role of adjustments in livelihood strategies

To test the hypothesis that adjustments in livelihood strategies play a role in the pathway from agricultural production gains to food security, we apply a Causal Mediation Analysis (CMA). CMA methods aim at pinning down the mechanisms – mediators – through which a treatment has an impact on an outcome. The methods consist in proposing and testing whether a particular mediator plays a role in the causal chain (Imai, Keele and Tingley, 2010). Mediation analysis has been widely used in the economic literature and in diverse domains such as education (Powdthavee, Lekfuangfu and Wooden, 2013; Chen, Chen and Liu, 2019; Bijwaard and Jones, 2019), health (Conti, Heckman and Pinto, 2016; Brunello *et al.*, 2016; Bellani and Bia, 2019) or labour (Huber, Lechner and Mellace, 2017). In agricultural contexts, CMA has been recently employed by Bellemare, Lee and Novak (2021) for a contract farming analysis in Madagascar, and by Pace *et al.* (2022) as part of a cash transfer impact evaluation in Zimbabwe.

CMA methods typically follow a two-step approach. The first step consists in estimating the overall impact of the treatment on the outcome, as any standard impact evaluation method. In the case of this paper, this first step is to estimate equation (2) for food security outcomes.

The second step consists in assessing whether the mediator is a mechanism (or the only mechanism) through which the treatment impacts the outcome:

$$\begin{cases} M_{idt} = \alpha_2 + \beta_2 T_{dt} + \gamma_i + \gamma_t + \delta_2 X_{idt} + \varepsilon_{2_{idt}} & (3) \\ Y_{idt} = \alpha_3 + \beta_3 T_{dt} + \mu_3 M_{idt} + \gamma_i + \gamma_t + \delta_3 X_{idt} + \varepsilon_{3_{idt}} & (4) \end{cases}$$

From equations (2), (3), and (4) we recover a series of parameters. $\hat{\beta}_1$ is the total effect of ATA's agricultural interventions on food security, decomposable into the direct effect, $\hat{\beta}_3$, and the indirect effect, $\hat{\beta}_2 \times \hat{\mu}_3$. The former captures the effect of ATA's agricultural interventions on food security controlling for the mediator variable and the set of confounding factors. The latter captures the effect of ATA's agricultural interventions on food security that is mediated by the mediator variable. This indirect effect is the product of the effect of ATA's agricultural interventions on the mediator variable and the partial effect of the mediator variable on food security.

The main identification assumption of CMA is sequential ignorability, which implies that (i) treatment assignment should be (conditionally) exogenous to the outcome and mediator, and (ii) conditional on treatment assignment and pre-treatment covariates, the mediator should be exogenous to the outcome. In our context, the second part of the assumption is unlikely to hold as higher food security is likely positively correlated with adjustments in livelihood strategies. We follow Imai *et al.* (2011) and instrument the mediator variable using a set of exclusion restriction variables selected as for their potential to explain livelihoods diversification opportunities faced by households without being direct predictors of food security: (i) an indicator for households living in a community with a job cooperative, taken as an indicator of greater job opportunities in the community and thus a pull factor of livelihoods diversification (Barrett, Reardon and Webb, 2001); (ii) an indicator for households having an active working age member with some secondary education, pointing to potential qualified labour supply for

off-farm work (Eshetu and Mekonnen, 2016; Gebru, Ichoku and Phil-Eze, 2018); (iii) the interaction of (i) and (ii); (iv) an indicator for households having a mobile phone, signalling potential better access to job market information, financial services and communication that offer greater off-farm work possibilities (Leng *et al.*, 2020; Min, Liu and Huang, 2020); and (v) the interaction of (i) and (iv).[18,19]

[18] We apply these instruments in a Control Function (CF) approach that uses more information and improves the precision of the estimates in comparison to the basic two-stage least squares approach (Heckman and Robb, 1985; Wooldridge, 2015).

[19] To check the sensitivity of the results to this specification, we also consider as an instrument an indicator for households' access to electricity – reflecting rural infrastructural investments that affect the economic environment – and its interaction with the indicator for living in a community with a job cooperative. First stage results reported in Annex Table A12 justify the validity of the instruments. Indeed, for both the main and alternative sets of exclusion restriction variables, results from the F-test of joint significance of excluded instruments reported in the bottom panel show that instruments are relevant.

5 Main results

5.1 Impact on agricultural yields

We first estimate the impact of ATA's agricultural interventions on agricultural yields, proxied by NDVI, while considering both the months of the main growing period (from June to October) as well as alternate measurement periods from June to August to June to December. Table 2 reports the results of these estimations. For all periods considered, ATA's agricultural interventions are significantly associated with a higher NDVI and the coefficient for the main growing period in column 3 suggests that ATA's agricultural interventions increased NDVI by about 1 percent. Given the magnitude of the correlation between NDVI and cereal yields (Table A2), the treatment effect on NDVI is equivalent to an increase of cereal yields of about 2.8 percent.

Table 2. Impact on NDVI

	1 June to August	2 June to September	3 June to October	4 June to November	5 June to December
Treated	0.005**	0.004*	0.005***	0.004**	0.004***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
District fixed effects	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES
Covariates	YES	YES	YES	YES	YES
Adjusted R2	0.25	0.26	0.17	0.13	0.13
Control mean in 2011	0.51	0.53	0.55	0.55	0.55
Control mean in 2016	0.53	0.54	0.55	0.55	0.54
Districts	624	624	624	624	624
Observations	3 744	3 744	3 744	3 744	3 744

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Models correct for inverse probability weighting adjustment and control for population and rainfall anomaly (measured over the same period as NDVI). Addis Ababa region excluded.

Source: Authors' own elaboration.

5.2 Impact on food security

Increases in agricultural yields are likely to translate into higher food security among rural households living in treated districts. We thus estimate the impact of ATA's agricultural interventions on food security indicators. Table 3 reports the results and shows that, overall, ATA's agricultural interventions are associated with improved food security outcomes. First, the likelihood of experiencing a food gap falls by 6.5 percentage points and the duration in months of that gap declines by 0.7 months, indicating greater stability in access to food. Second, while the HDD score is insignificant and of a small magnitude indicating the number of food groups consumed did not change much, the significant increase in the FCS of 2.6 points suggests treated households shifted towards a more nutrient rich diet. Finally, total household food consumption in monetary terms increases by close to 16 percentage points, pointing to an

improvement in the quantity and/or quality of food intake. Altogether, these results provide robust evidence that ATA's interventions led to improvements in household access to food and dietary quality.

Table 3. Impact on food security

	1 Food gap	2 Months of food gap	3 Household Dietary Diversity	4 Food Consumption Score	5 Total food consumption
Treated	-0.066*	-0.680**	0.085	2.662**	0.159***
	(0.036)	(0.342)	(0.117)	(1.216)	(0.050)
Household fixed effects	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES
Covariates	YES	YES	YES	YES	YES
Adjusted R2	0.03	0.05	0.04	0.02	0.06
Control mean in 2011/12	0.31	2.96	4.88	42.33	7.65
Control mean in 2015/16	0.36	3.63	5.33	43.40	7.32
Districts	230	219	230	230	230
Households	3 212	1 771	3 213	3 213	3 208
Observations	9 176	2 886	9 208	9 208	8 866

Notes: * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors clustered at the district level reported in parentheses. Models correct for inverse probability weighting adjustment. Covariates include those described in Section 4.3. "Months of food gap" is conditional on having experienced food gap in past 12 months. "Total food consumption" is expressed in log.

Source: Authors' own elaboration.

5.3 Impact on livelihood strategies

As described in the conceptual framework, the higher yields promoted by ATA's agricultural interventions also have the potential to translate into livelihood strategy adjustments. We thus estimate the impact of ATA's agricultural interventions on labour strategies (Table 4) and migration (Table 5).

Table 3 shows that ATA's agricultural interventions are associated with a close to 5 percentage point higher likelihood of opportunity-led off-farm participation and a 6 percentage points lower likelihood of on-farm specialization. The positive and significant treatment effect on opportunity-led off-farm and the negative and significant treatment effect on on-farm specialization suggest that ATA's agricultural interventions are providing the impetus for a certain set of rural households to shift out of agriculture, potentially to exploit the comparative advantage of their resource base: be it in terms of assets, labour or skills. The magnitude of the treatment effect is not substantial; however, if measured against the low baseline participation levels in opportunity-led off-farm activities, the treatment effect is instead of a notable magnitude, accounting for a close to 15 percent increase in participation. Indeed, whereas one component

of the agricultural transformation agenda is to modernize and improve the productivity of the agricultural sector, the strengthening of other sectors of the economy is another component; this finding thus contributes to the evidence base of ATA's support towards agricultural transformation in Ethiopia.

Table 4. Impact on labour strategies

	1 No labour activity	2 On-farm specialization	3 Survival-led off-farm	4 Opportunity-led off-farm
Treated	0.006	-0.058*	0.008	0.045**
	(0.015)	(0.035)	(0.031)	(0.022)
Household fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Covariates	YES	YES	YES	YES
Adjusted R2	0.02	0.03	0.03	0.01
Control mean in 2011/12	0.07	0.49	0.13	0.31
Control mean in 2015/16	0.11	0.50	0.12	0.27
Districts	230	230	230	230
Households	3 213	3 213	3 213	3 213
Observations	9 208	9 208	9 208	9 208

Notes: * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors clustered at the district level reported in parentheses. Models correct for inverse probability weighting adjustment. Covariates include those described in Section 4.3.

Source: Authors' own elaboration.

Table 5 column 1 shows that ATA's agricultural interventions are associated with a higher likelihood of migration by about 5 percentage points. As migration information in ESS 2011/12 is likely underestimated,[20] column 2, replicates the analysis restricting the analysis to ESS 2013/14 and ESS 2015/16 (and excluding households treated in 2013/14). While the coefficient is somehow lower and less precisely estimated, the pattern is similar: ATA's agricultural interventions seem associated with a higher likelihood of migration. Overall, this finding further contributes to the evidence that ATA's agricultural interventions supported some adjustments in the livelihood strategies of smallholder farmers by promoting labour mobility.

[20] As ESS 2011/12 is the first wave of the panel, no information on the household members who left since a previous wave is collected.

Table 5. Impact on migration

	1 **Any migration** All waves	2 **Any migration** Excluding wave 1
Treated	0.050**	0.026
	(0.019)	(0.020)
Household fixed effects	YES	YES
Year fixed effects	YES	YES
Covariates	YES	YES
Adjusted R2	0.32	0.15
Control mean in 2011/12	0.05	
Control mean in 2013/14	0.31	0.31
Control mean in 2015/16	0.45	0.45
Districts	230	206
Households	3 213	2 812
Observations	9 208	5 503

Notes: * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors clustered at the district level reported in parentheses. Models correct for inverse probability weighting adjustment. Covariates include those described in Section 4.3. Column 1 includes all three waves. Column 2 restricts to wave 2 and 3, while ignoring households treated in wave 2.

Source: Authors' own elaboration.

6 Exploring pathways

6.1 Mediation effects

The total effect on food security potentially comprises both a direct effect – from higher agricultural yields to better food security – and an indirect effect – mediated by adjustments in rural households' livelihood strategies. To explore the potential mediating role of adjustments in livelihood strategies, we implement a mediation analysis considering both the higher participation in opportunity-led off-farm activities and migration promoted by ATA's agricultural interventions as potential mediating factors in the causal chain from higher yields to better food security.

Tables 6 and 7 show the effect of ATA's agricultural interventions on food security indicators while reporting, in the bottom panel, the direct effect, the indirect effect and the total effect emerging from the causal mediation analysis. The direct effect captures how ATA's agricultural interventions impact food security through improvements in agricultural yields, accounting for the potential mediating role of adjustments in livelihood strategies. The indirect effect captures the effect of ATA's agricultural interventions on food security that is mediated by adjustments in livelihood strategies. The total effect is the sum of the direct and indirect effect. The results demonstrate that neither opportunity-led off-farm nor migration seem to mediate the impact of ATA's agricultural interventions on food security. Across all estimations for each mediator, the indirect effect is not significantly different from zero.[21] Results thus suggest that the production expansion generated by ATA's agricultural interventions in the agricultural system fully drives ATA's impact on food security outcomes.

[21] Results are consistent when considering the specification with an alternative set of instruments.

Table 6. Mediating role of opportunity-led off-farm on food security

	1 Food gap	2 Months of food gap	3 Household Dietary Diversity	4 Food Consumption Score	5 Total food consumption
Treated	-0.043	-0.730*	0.033	1.887	0.126**
	[0.035]	[0.378]	[0.125]	[1.256]	[0.055]
Opportunity-led off-farm	-0.521	1.935	1.172	17.455	0.731*
	[0.354]	[4.467]	[1.172]	[12.022]	[0.428]
Household fixed effects	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES
Covariates	YES	YES	YES	YES	YES
Direct effect	-0.04	-0.73**	0.03	1.89	0.13**
Indirect effect	-0.02	0.08	0.05	0.75	0.03
Total effect	-0.07*	-0.65*	0.08	2.64**	0.16***
Adjusted R2	0.02	0.06	0.04	0.02	0.06
Control mean in 2011/12	0.31	2.96	4.88	42.33	7.65
Control mean in 2015/16	0.36	3.63	5.33	43.40	7.32
Districts	230	219	230	230	230
Households	3 212	1 771	3 213	3 213	3 208
Observations	9 176	2 886	9 208	9 208	8 866

Notes: * p<0.1, ** p<0.05, *** p<0.01. Jacknife standard errors clustered at the district level reported in brackets. Models correct for inverse probability weighting adjustment. Covariates include those described in Section 4.3. “Months of food gap” is conditional on having experienced food gap in past 12 months. “Total food consumption” is expressed in log.

Source: Authors’ own elaboration.

Table 7. Mediating role of migration on food security

	1 Food gap	2 Months of food gap	3 Household Dietary Diversity	4 Food Consumption Score	5 Total food consumption
Treated	-0.060	-0.509	0.016	2.463*	0.145***
	[0.041]	[0.426]	[0.125]	[1.351]	[0.052]
Any migration	-0.136	-3.616	1.408	4.058	0.256
	[0.198]	[2.884]	[1.180]	[8.891]	[0.350]
Household fixed effects	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES
Covariates	YES	YES	YES	YES	YES
Direct effect	-0.06	-0.51	0.02	2.46*	0.15***
Indirect effect	-0.01	-0.19	0.07	0.21	0.01
Total effect	-0.07*	-0.70*	0.09	2.67**	0.16***
Adjusted R2	0.02	0.06	0.04	0.02	0.07
Control mean in 2011/12	0.31	2.96	4.88	42.33	7.65
Control mean in 2015/16	0.36	3.63	5.33	43.40	7.32
Districts	230	219	230	230	230
Households	3 212	1 771	3 213	3 213	3 208
Observations	9 176	2 886	9 208	9 208	8 866

Notes: * p<0.1, ** p<0.05, *** p<0.01. Jacknife standard errors clustered at the district level reported in brackets. Models correct for inverse probability weighting adjustment. Covariates include those described in Section 4.3. "Months of food gap" is conditional on having experienced food gap in past 12 months. "Total food consumption" is expressed in log.

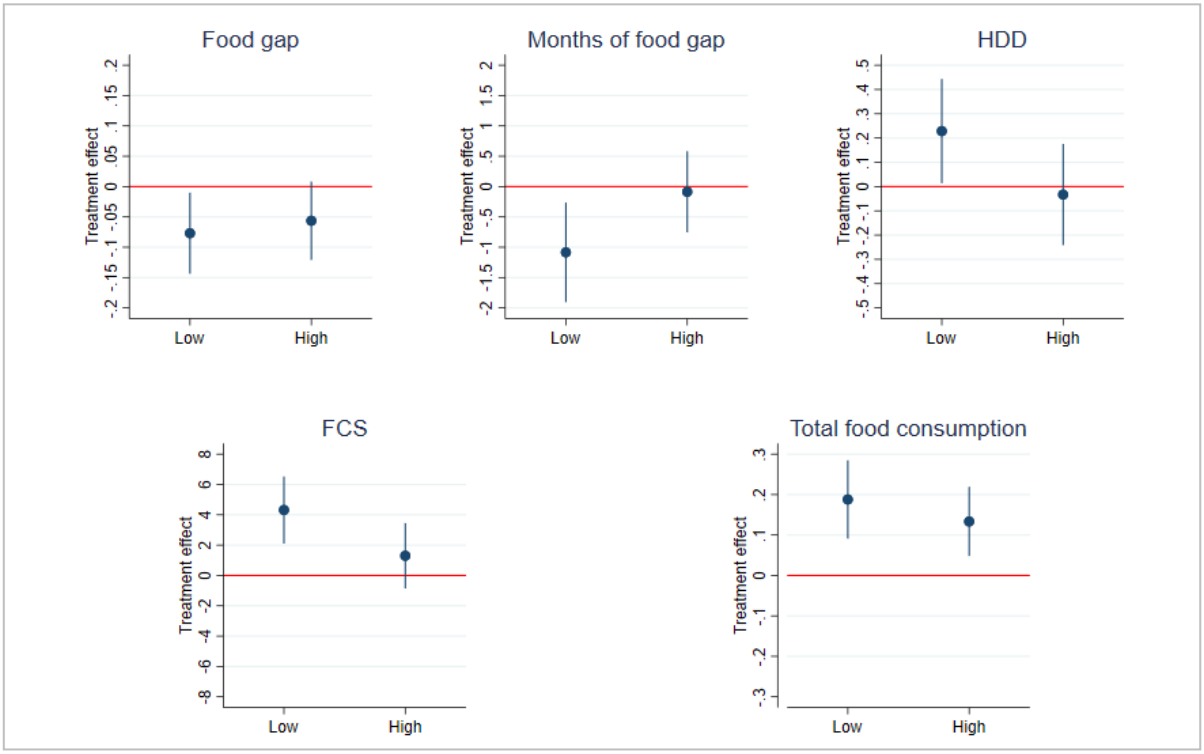
Source: Authors' own elaboration.

6.2 Heterogeneity analysis

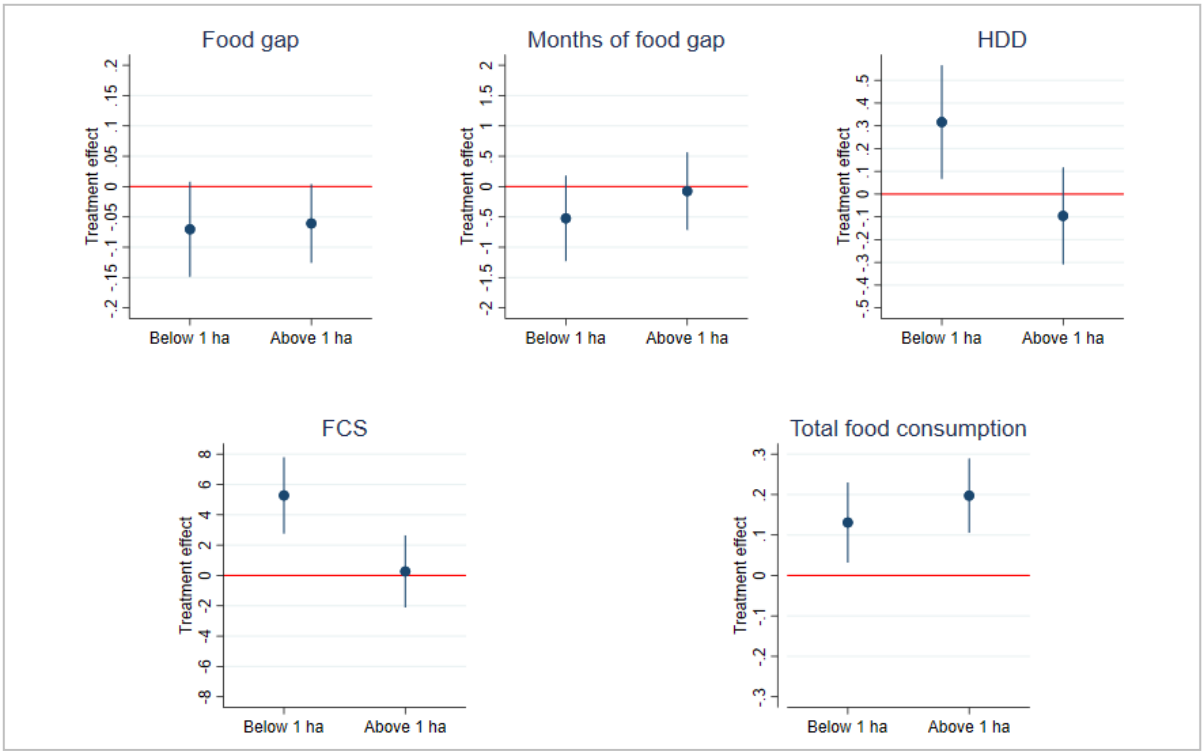
The absence of evidence that adjustments in livelihood strategies played a mediating role in the food security impacts could suggest that different types of households benefit on the two margins. To explore this, Figures 3 and 4 report food security and livelihood impacts while distinguishing across assets and land endowment. Results suggest that food security impacts are somehow concentrated among rural households with low agricultural assets and land endowment, while livelihood impacts are somehow concentrated among rural household with high agricultural assets and land endowment. Those findings thus provide suggestive evidence that the effects of higher yields vary across different types of households. Among worse-off households that are more likely to suffer from severe food insecurity, higher yields primarily translated into higher food security. In contrast, among better-off households for whom food insecurity is likely less severe, higher yields primarily translated into adjustments in livelihood strategies.

Figure 3. Food security impacts by assets and land endowment

a. Treatment effects by agricultural assets endowment



b. Treatment effects by landholdings

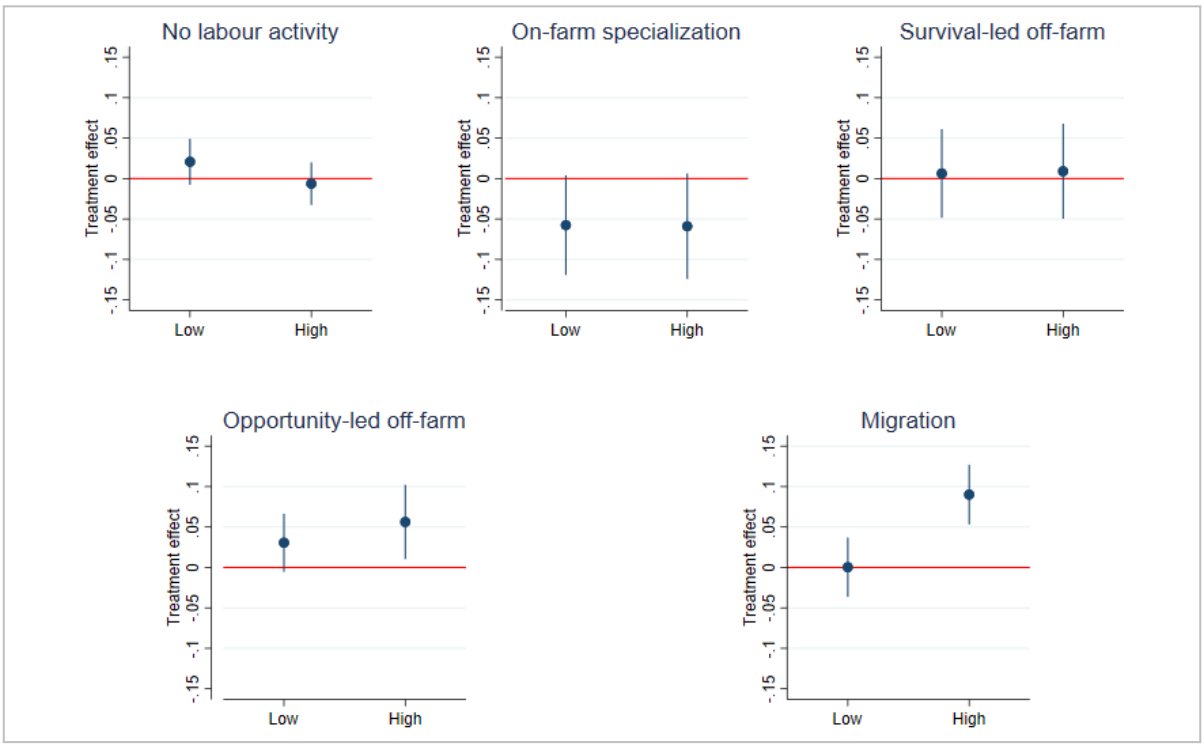


Notes: Bars represent 90 percent confidence intervals. Assets endowment is captured by an assets wealth index computed through principal component analysis on considering agricultural assets. “Low” and “High” refer to being below or above the median.

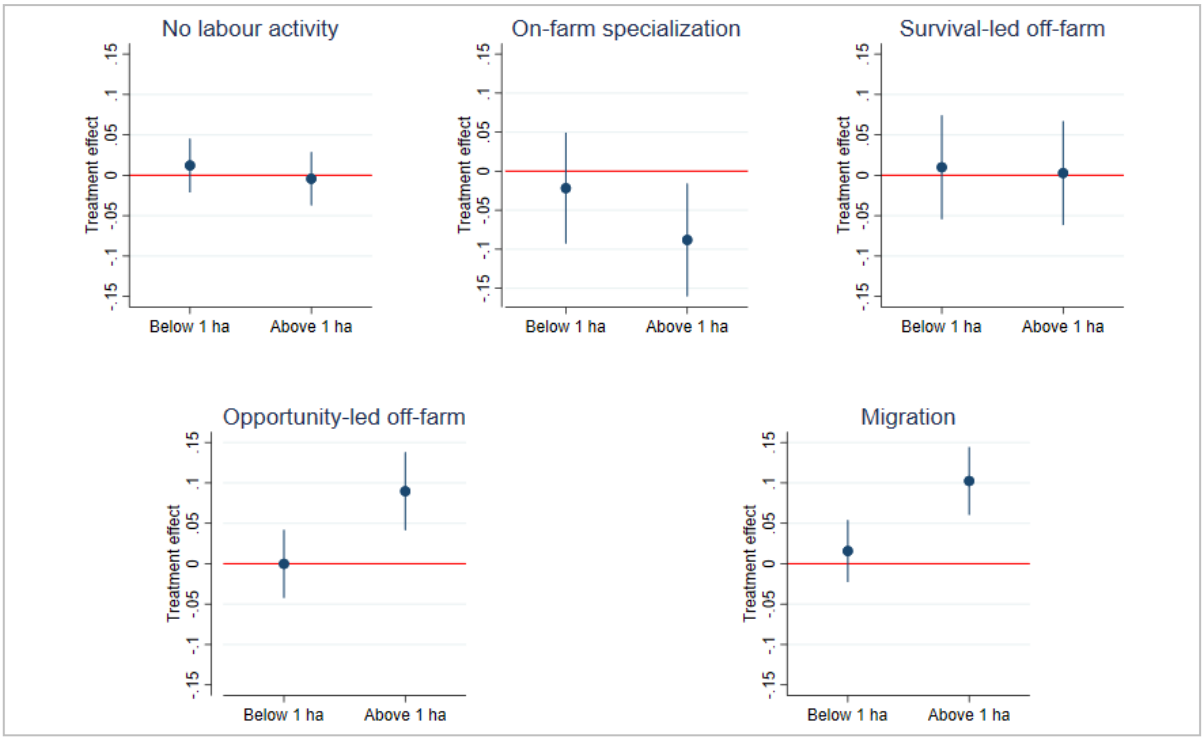
Source: Authors’ own elaboration.

Figure 4. Livelihood impacts by assets and land endowment

a. Treatment effects by agricultural assets endowment



b. Treatment effects by landholdings



Notes: Bars represent 90 percent confidence intervals. Assets endowment is captured by an assets wealth index computed through principal component analysis on considering agricultural assets. “Low” and “High” refer to being below or above the median.

Source: Authors’ own elaboration.

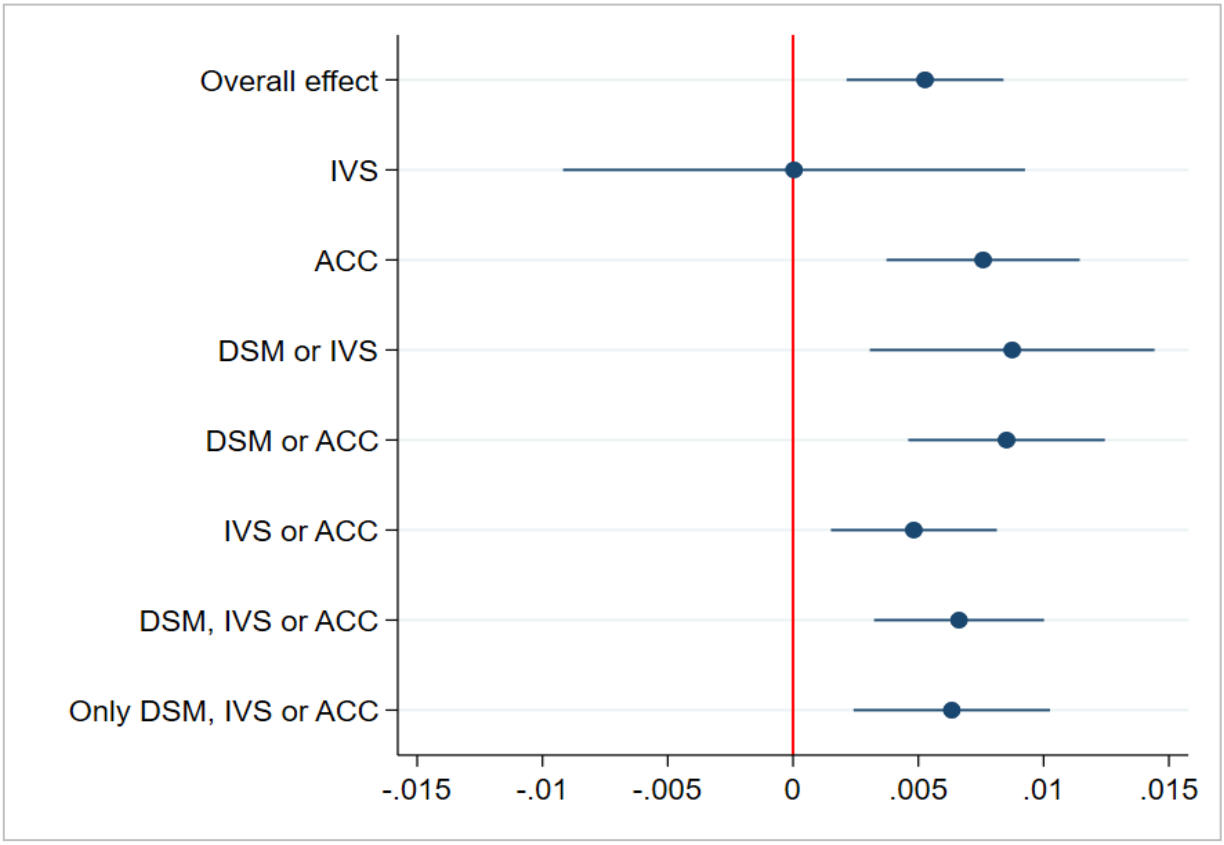
6.3 Decomposing treatment

The treatment variable defined so far captures multiple, heterogeneous agricultural interventions implemented by ATA. Being able to identify which agricultural interventions work best is crucial for improving policy design and extending recommendations to other contexts. Fully separating the role of each ATA intervention is not possible as seventy different combinations exist from the nine interventions implemented by ATA between 2011 and 2016. However, it is possible to explore the role of ATA's largest-scale interventions by focusing on DSM, IVS and ACC. About 90 percent of treated districts were targeted by at least one of these three interventions and almost 60 percent of treated districts were targeted only by one or a combination of these three interventions.

Figure 5 reports the results of estimating treatment effects on agricultural yields for seven combinations of the three major ATA interventions.[22] We find positive and significant treatment effects for six of the treatment combinations. Results demonstrate that DSM and ACC each have a positive, standalone effect, in contrast to IVS. These results also suggest the existence of complementarities across interventions. For example, results show that the point estimate for being targeted by DSM or ACC is slightly higher than the point estimate for being treated only by ACC. These outcomes highlight that combining interventions that address supply and demand bottlenecks in the agricultural system can contribute to important changes in agricultural productivity.

[22] To perform this analysis, we construct a valid counterfactual for each treatment decomposition as described in Section 4.3. In contrast to the main analysis, and to compare against a pure counterfactual, we exclude from the control group all districts targeted by other ATA interventions than the treatment decomposition of interest. Given the lower coverage of DSM, the propensity score estimation does not perform well for the DSM treatment decomposition. We thus do not report results for the DSM treatment decomposition but compare results for treatment decompositions with and without DSM to provide insights on its separate effect.

Figure 5. Decomposing treatment on NDVI (main growing period)



Notes: Bars represent 90 percent confidence intervals. NDVI is computed over the months of the main growing period (June to October). Models correct for inverse probability weighting adjustment and control for population and rainfall anomaly (for the main growing period). Addis Ababa region excluded.

Source: Authors' own elaboration.

6.4 Spatial effects

Widespread agricultural interventions such as those implemented by ATA have the potential to translate into both spatial spillover and agglomeration effects.

Positive spillover effects may occur as investments made in treated districts may also benefit adjacent districts by simulating output markets or input and service provision markets. On the other hand, negative spillover effects may arise if investments made in treated districts crowd out investments or deteriorate the competitive advantage of output markets and input and service provision markets in adjacent districts. The presence of spillover effects could be observed on the same outcome variables for which we are assessing ATA's impacts, which would bear implications for the estimation of the average treatment effect. To explore the existence of such effects, we estimate the effect on agricultural yields of being adjacent to a treated district.[23] Columns 1 and 2 of Table 8 report the results of this analysis. Column 1 includes both treated and control districts and the column 2 restricts the estimation to control districts only. In both cases, results demonstrate that having an adjacent treated district has no effect on NDVI. In addition to excluding the existence of positive spillover effects, this result

[23] Exploring the existence of spillover effects on food security and livelihood strategies is not feasible since ESS data only represent a subset of districts, reducing the number of adjacent districts, and raising issues of potential selection bias.

gives confidence that the positive treatment effect found for agricultural yields is not driven by specific local advantages of some areas but actually reflects the true effect of ATA's agricultural interventions.

Agglomeration effects are likely to occur since a main feature of ATA's agricultural interventions is that they are based on a geographic clustering approach. Treated districts may thus benefit even more from being adjacent to other treated districts. To explore the existence of agglomeration effects, column 3 of Table 8 estimates the effect on NDVI of the interaction between being treated and having an adjacent district treated. Results point toward the existence of agglomeration effects, given the positive and significant coefficient on the interaction between being treated and having an adjacent district treated.[24] Since relatively few treatment districts are not bordered by another treatment district, the average treatment effect is measured with somewhat less precision. Nevertheless, when considering agglomeration treatment effects relative to treatment in isolation, we estimate an increase in NDVI of 0.026, which is equivalent to an increase in cereals yields of nearly 15 percent. Despite the small size of the set of districts treated in isolation, this effect is indicative of the potential efficiency of the ATA clustering approach and suggestive of the potential for complementary studies to robustly assert the mechanisms through which agglomeration strategies can enhance agricultural outcomes.

Table 8. Spatial effects – NDVI for the main growing period

	1	2	3
	Spillover effects		Agglomeration effects
	All districts	Control districts	
Treated			-0.019***
			(0.007)
Adjacent district treated	0.001	-0.003	-0.002
	(0.002)	(0.003)	(0.002)
Treated x adjacent district treated			0.026***
			(0.007)
District fixed effects	YES	YES	YES
Year fixed effects	YES	YES	YES
Covariates	YES	YES	YES
Adjusted R2	0.17	0.20	0.18
Control mean in 2011	0.54	0.54	0.55
Control mean in 2016	0.55	0.55	0.55
Districts	624	297	624
Observations	3 744	1 782	3 744

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. NDVI is computed over the months of the main growing period (June to October). Models correct for inverse probability weighting adjustment and control for population and rainfall anomaly (for the main growing period). Addis Ababa region excluded.

Source: Authors' own elaboration.

[24] For the same reasons as for spillover effects, exploring the existence of agglomeration effects on food security and livelihood strategies is not feasible using the ESS data.

7 Conclusions and discussion

Improvements in food security coming from better agricultural productivity and resilient livelihoods are at the core of Sustainable Development Goal 2 of Zero Hunger. Agricultural interventions promoting access and use of modern agricultural practices have the potential to play a key role in achieving this goal. However, the extent to which those agricultural interventions effectively translate into better food security outcomes, and in particular by motivating rural households to adjust their livelihoods toward more food secure strategies, is not well documented.

Exploiting the progressive roll-out of the interventions implemented by the Agricultural Transformation Agency of Ethiopia and combining various innovative sources of data, this paper shows that ATA's agricultural interventions led to higher agricultural yields and better food security. Using remote sensing data on the NDVI as a proxy for agricultural yields (Sultana *et al.*, 2014; Burke and Lobell, 2017; Moriondo, Maselli and Bindi, 2017, Lobell *et al.*, 2020; Panek and Gozdowski, 2021; Salazar *et al.*, 2021), we demonstrate that the interventions implemented by the ATA in Ethiopia over the 2012 to 2016 period were responsible for a significant increase in NDVI, with treatment effects equivalent to increases in cereals yields of 2.8 percent. In the case of cluster-based interventions, the yield gains were further enhanced relative to areas without clustering, reaching up to 15 percent, though measured with less precision. This notable increase in NDVI can be attributed to the numerous, coordinated interventions supported by ATA to modernize agricultural production practices, including widespread diffusion of improved seeds, systems to relax liquidity constraints for adopting modern inputs, improvements to irrigation infrastructure and techniques, and integration of the value chain for improved commercialization, among others. The same interventions were found to better household food security through improved access to food. Rural households in treatment districts secured greater total food consumption, a lower likelihood of gaps in their access to food, and improvements in the Food Consumption Score, a nutrient-weighted dietary diversity index.

Exploring the mediating role of adjustments in livelihood strategies, results indicate that ATA's agricultural interventions led to some adjustments in livelihood strategies. First, we observed a significant increase in engagement in opportunity-led off-farm activities. Second, an increase in the likelihood of investing in migration also emerged from the analysis. However, the mediation analysis did not demonstrate that these adjustments in livelihood strategies were on the causal pathway towards the food security impacts. Instead, heterogeneity analysis demonstrated that treatment effects are differentiated according to household asset and land endowments. In particular, food security effects were found to be concentrated among the most vulnerable rural households – those with low agricultural assets and land endowment – pointing to the welfare enhancing potential of the large-scale agricultural interventions supported by ATA. By contrast, adjustments in livelihood strategies emerged only for well-endowed rural households – those with high agricultural assets and land endowment. The findings are illustrative of the rural transformation potential of several large-scale agricultural interventions in sub-Saharan Africa. Overall, the effect of ATA's agricultural interventions on food security emerges as fully driven by higher agricultural yields, which were generated by the improvements in the agricultural system that facilitated access to seeds, and improved commercialization channels, as supported by the DSM project and the ACC initiative.

The dichotomous manner in which outcomes emerged brings to light certain key features of rural transformation in Ethiopia and the role of ATA in advancing such transformation. From a

production perspective, results indicate that food supply was a major challenge experienced by small-scale producers in Ethiopia, and that even small improvements in yields have the potential to generate relevant improvements in household food security, and in particular, among the most vulnerable groups. ATA's interventions were not poverty or vulnerability-targeted; however, by targeting specific commodities of relevance to household food security, improvements emerged in terms of strengthened consumption outcomes. This is the result not only of the largely consumption-oriented nature of household production strategies, but also because the bottlenecks ATA sought to address were common across all categories of small-scale producers. Looking forward, as such bottlenecks are removed, the challenges faced by rural producers may be less homogenous, and attaining comparable food security improvements among vulnerable groups through ATA-type interventions will require specific targeting of interventions to those population groups according to their needs and challenges.

While ATA's interventions were effective at supporting food security through production gains, the discord between those outcomes and livelihoods diversification reflects a context where more than 90 percent of the rural population is agriculturally-oriented and most diversification occurs in the form of temporary labour. The disproportionate orientation in agriculture may also be the outcome of the limited development of agricultural value chains and the rural infrastructure and services overall, which places a ceiling on the extent to which downstream linkages from agricultural productivity gains are able to form and thrive. The heterogeneity analysis illustrated that the off-farm diversifiers were predominantly highly asset endowed and larger landholding households. Since ATA was not involved in influencing land allocations or in enhancing asset accumulation, those newly diversifying households were probably less in need to strengthening their food supply and thus better positioned to engage in off-farm diversification (through the liquidity or labour productivity improvements obtained from ATA interventions).

For diversification to be a broad-based strategy that is opportunity-led and supports food security through income effects, agricultural interventions, such as ATA's in a context such as Ethiopia, cannot be a singular route for improving resilience of rural livelihoods and overall rural transformation. Achieving greater opportunity-led livelihoods diversification may require strengthening agricultural value chains in such a way that small-scale producers' gain access and diversify their participation through wage employment via processing activities or service provision related to the value chain. Pairing production interventions with others that support those downstream linkages may be the route to enhancing the agricultural sector and create the conditions for a dynamic rural economy. For such value chain interventions to succeed, the stability of agricultural production is fundamental, which is where ATA's agricultural interventions have been arguably most relevant, as they demonstrably reduced food gaps in beneficiary areas.

Results from this working paper also point toward the opportunity to consider secondary effects when designing agricultural interventions given that the improvement of food security outcomes and adjustments in livelihood strategies were not originally intended. Better integrating those secondary effects as stated objectives in project design could establish a framework for guiding and monitoring those effects, and to safeguard against undesirable outcomes. The evidence that adjustments in livelihoods were concentrated among wealthier households highlights the need to foster an environment in which resource-poor households can acquire the means to strengthen livelihoods in addition to food security. Future project design could thus integrate specific targeting strategies to reach those marginal populations through appropriate mechanisms, serving not only to consolidate these livelihood improvements, but also present a sustainable pathway towards those objectives. In this regard, Ethiopia's Productive Safety Net

Programme (PSNP) is well placed to reaching the most vulnerable populations, addressing their specific production constraints while also protecting their food security.

Agricultural transformation is a complex transition from a subsistence farming sector to a high productivity agri-food sector requiring important shifts not only in the intensification and modernization of the agricultural system, but also the rise of urbanization and the strengthening of ties between agriculture and other sectors of the economy. An important challenge in this transformation is ensuring the inclusiveness of the transition, such that vulnerable groups also gain from the improvements in the agricultural economy. ATA's agricultural interventions have arguably advanced the agricultural transformation process in Ethiopia, and notably in terms of gains marked by the agricultural sector. The interventions were successful in improving the livelihoods of smallholder farmers overall, and notably among the poorest and least land endowed.

References

Abate, G. T., Bernard, T., de Brauw, A. & Minot, N. 2018. The impact of the use of new technologies on farmers' wheat yield in Ethiopia: Evidence from a randomized control trial. *Agricultural Economics*, 49(4): 409–421. https://doi.org/10.1111/agec.12425

ATA (Agricultural Transformation Agency). 2021. About Us. In: *Agricultural Transformation Agency*, Addis Ababa. Cited 29 November 2021. www.ata.gov.et

ATA. 2017. *Agricultural Commercialization Clusters Initiative: Design, Implementation Approach, Focus Value Chains, Interventions, and Cluster Strategies*, Addis Ababa.

Asfaw, S., Scognamillo, A., Di Capria, G., Sitko, N. & Ignaciuk, A. 2019. Heterogeneous impact of livelihood diversification on household welfare: Cross-country evidence from Sub-Saharan Africa. *World Development*, 117: 278–295. https://doi.org/10.1016/j.worlddev.2019.01.017

Athey, S. & Imbens, G. 2006. Identification and inference in nonlinear difference-in-differences models. *Econometrica,* 74(2): 431–497. https://doi.org/10.1111/j.1468-0262.2006.00668.x

Atlas AI. 2021. *Asset Wealth Index 2010*.

Austin, P.C. 2011. An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multivariate Behavioral Research,* 46(3): 399–424. https://doi.org/10.1080/00273171.2011.568786

Awotide, B.A., Karimov, A., Diagne, A. & Nakelse, T. 2013. The impact of seed vouchers on poverty reduction among smallholder rice farmers in Nigeria. *Agricultural economics*, 44(6): 647–658. https://doi.org/10.1111/agec.12079

Babatunde, R.O. & Qaim, M. 2010. Impact of off-farm income on food security and nutrition in Nigeria. *Food policy*, 35(4): 303–311. https://doi.org/10.1016/j.foodpol.2010.01.006

Bachewe, F., Berhane, G., Minten, B. & Taffesse, A.S. 2020. Nonfarm income and rural labor markets. In: Dorosh and Minten, eds. *Ethiopia's Agrifood System: Past Trends, Present Challenges, and Future Scenarios*. Washington, DC, IFPRI. https://doi.org/10.2499/9780896296916_11

Baker, S., Larcker, D.F. & Wang, C.C.Y. 2021. *How Much Should We Trust Staggered Difference-in-Differences Estimates?.* ECGI Finance Working Paper N° 736/2021. https://doi.org/10.1016/j.jfineco.2022.01.004

Barrett, C.B., Reardon, T. & Webb, P. 2001. Nonfarm income diversification and household livelihood strategies in rural Africa: concepts, dynamics, and policy implications. *Food Policy*, 26(4): 315–331. https://doi.org/10.1016/S0306-9192(01)00014-8

Bellani, L. & Bia, M. 2019. The long-run effect of childhood poverty and the mediating role of education. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 182(1): 37–68. https://doi.org/10.1111/rssa.12388

Bellemare, M.F., Lee, Y.N. & Novak, L. 2021. Contract farming as partial insurance. *World Development*, 140, 105274. https://doi.org/10.1016/j.worlddev.2020.105274

Bellemare, M.F. & Wichman, C.J. 2020. Elasticities and the inverse hyperbolic sine transformation. *Oxford Bulletin of Economics and Statistics*, 82(1): 50-61. https://doi.org/10.1111/obes.12325

Bezu, S., Barrett, C.B. & Holden, S. T. 2012. Does the nonfarm economy offer pathways for upward mobility? Evidence from a panel data study in Ethiopia. *World Development*, 40(8): 1634–1646. https://doi.org/10.1016/j.worlddev.2012.04.019

Bijwaard, G.E. & Jones, A.M. 2019. An IPW estimator for mediation effects in hazard models: with an application to schooling, cognitive ability and mortality. *Empirical Economics*, 57(1): 129–175. https://doi.org/10.1007/s00181-018-1432-9

Bizikova, L., Jungcurt, S., McDougal, K. & Tyler, S. 2020. How can agricultural interventions enhance contribution to food security and SDG 2.1?. *Global Food Security*, 26, 100450. https://doi.org/10.1016/j.gfs.2020.100450

Block, S. & Webb, P. 2001. The dynamics of livelihood diversification in post-famine Ethiopia. *Food policy*, 26(4): 333–350. https://doi.org/10.1016/S0306-9192(01)00015-X

Borusyak, K. & Jaravel, X. 2017. *Revisiting Event Study Designs, with an Application to the Estimation of the Marginal Propensity to Consume.* Technical report, Department of Economics, Harvard University.

Brunello, G., Fort, M., Schneeweis, N. & Winter-Ebmer, R. 2016. The causal effect of education on health: what is the role of health behaviors?. *Health Economics*, 25(3): 314–336. https://doi.org/10.1002/hec.3141

Burke, M. & Lobell, D.B. 2017. Satellite-based assessment of yield variation and its determinants in smallholder African systems. *Proceedings of the National Academy of Sciences*, 114(9): 2189–2194. https://doi.org/10.1073/pnas.1616919114

Bustos, P., Caprettini, B. & Ponticelli, J. 2016. Agricultural productivity and structural transformation: Evidence from Brazil. *American Economic Review*, 106(6): 1320–65. https://doi.org/10.1257/aer.20131061

Callaway, B. & Sant'Anna, P.H. 2021. Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2): 200–230. https://doi.org/10.1016/j.jeconom.2020.12.001

CSA (Central Statistical Agency of Ethiopia) & World Bank. 2012. *ERSS Basic Information Document*. Ethiopia.

CSA. 2012. Ethiopia Rural Socioeconomic Survey 2011-2012, Wave 1, Ref: ETH_2011_ERSS_v02_M. In: *World Bank*. Washington, DC. Cited 21 April 2020 https://microdata.worldbank.org/index.php/catalog/2053/get-microdata.

CSA. 2014. Ethiopia Socioeconomic Survey 2013-2014, Wave 2, Ref: ETH_2013_ESS_v03_M. In: *World Bank*. Washington, DC. Cited 21 April 2020 https://microdata.worldbank.org/index.php/catalog/2247/get-microdata.

CSA. 2016. Ethiopia Socioeconomic Survey 2015-2016, Wave 3, Ref: ETH_2015_ESS_v03_M. In: *World Bank*, Washington, DC. Cited 21 April 2020 https://microdata.worldbank.org/index.php/catalog/2783/get-microdata.

Chen, S.H., Chen, Y.C. & Liu, J.T. 2019. The impact of family composition on educational achievement. *Journal of Human Resources*, 54(1): 122–170. https://doi.org/10.3368/jhr.54.1.0915.7401R1

Conti, G., Heckman, J.J. & Pinto, R. 2016. The effects of two influential early childhood interventions on health and healthy behaviour. *The Economic Journal*, 126(596): F28–F65. https://doi.org/10.1111/ecoj.12420

Covarrubias, K.A., de la O Campos, A.P. & Cordonnier, V. 2021. *Enhancing the inclusiveness of agro-commodity procurement zones in Ethiopia – National poverty profile.* FAO Agricultural Development Economics Technical Study No. 15. Rome, FAO. https://doi.org/10.4060/cb7980en

De Chaisemartin, C. & D'Haultfoeuille, X. 2020. Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9): 2964–96. https://doi.org/10.1257/aer.20181169

Devereux, S. 2000. *Food insecurity in Ethiopia, A discussion paper for DFID.* Institute of Development Studies, Sussex.

Didan, K. 2015. MOD13Q1 MODIS/Terra Vegetation Indices 16-Day L3 Global 250m SIN Grid V006 [Data set]. NASA EOSDIS Land Processes DAAC. In: *U.S. Geological Survey*. Reston. Cited 27 January 2022. https://doi.org/10.5067/MODIS/MOD13Q1.006

Dorosh, P. & Minten, B. 2020. *Ethiopia's Agrifood System: Past Trends, Present Challenges, and Future Scenarios.* Washington, DC, IFPRI.

Ellis, F. 2000. The Determinants of Rural Livelihood Diversification in Developing Countries. *Journal of Agricultural Economics*, 51(2): 289–302. https://doi.org/10.1111/j.1477-9552.2000.tb01229.x

Emerick, K. 2018. Agricultural productivity and the sectoral reallocation of labor in rural India. *Journal of Development Economics*, 135: 488–503. https://doi.org/10.1016/j.jdeveco.2018.08.013

ESA (European Space Agency). 2017. Land Cover CCI Product User Guide Version 2. Tech. Rep. In: *UCL-Geomatics*, Louvain. Cited 28 March 2022. maps.elie.ucl.ac.be/CCI/viewer/download/ESACCI-LC-Ph2-PUGv2_2.0.pdf

Eshetu, F., & Mekonnen, E. 2016. Determinants of off farm income diversification and its effect on rural household poverty in Gamo Gofa Zone, Southern Ethiopia. *Journal of Development and Agricultural Economics*, 8(10): 215–227. https://dx.doi.org/10.5897/jdae2016-0736

FAO. 2020. *Ten years of the Ethiopian Agricultural Transformation Agency. An FAO evaluation of the Agency's impact on agricultural growth and poverty reduction.* Rome. https://doi.org/10.4060/cb2422en

FAO & IIASA (International Institute for Applied Systems Analysis). 2021. Global Agro Ecological Zones version 4 (GAEZ v4). In: *FAO*, Rome. Cited 2 August 2021. www.fao.org/gaez/

Foster, A.D. & Rosenzweig, M.R. 2007. Economic development and the decline of agricultural employment. *Handbook of Development Economics*, 4: 3051–3083. https://doi.org/10.1016/S1573-4471(07)04047-8

Funk, C.C., Peterson, P.J., Landsfeld, M.F., Pedreros, D.H., Verdin, J.P., Rowland, J.D., Romero, B.E., Husak, G.J., Michaelsen, J.C. & Verdin, A.P. 2014. A quasi-global precipitation time series for drought monitoring: U.S. Geological Survey Data Series 832. In: *U.S. Geological Survey*. Reston. http://pubs.usgs.gov/ds/832

Gazeaud, J. & Stephane, V. 2022. Productive Workfare? Evidence from Ethiopia's Productive Safety Net Program. *American Journal of Agricultural Economics*, 1–26. https://doi.org/10.1111/ajae.12310

Gebru, G. W., Ichoku, H. E., & Phil-Eze, P. O. 2018. Determinants of livelihood diversification strategies in Eastern Tigray Region of Ethiopia. *Agriculture & Food Security*, 7(1): 1–9. https://doi.org/10.1186/s40066-018-0214-0

Gollin, D., Parente, S. & Rogerson, R. 2002. The role of agriculture in development. *American Economic Review*, 92(2): 160–164. https://doi.org/10.1257/000282802320189177

Goodman-Bacon, A. 2021. Difference-in-Differences with Variation in Treatment Timing. *Journal of Econometrics,* 225(2): 254–277. https://doi.org/10.1016/j.jeconom.2021.03.014

Haggblade, S., Hazell, P. & Reardon, T. 2010. The rural non-farm economy: Prospects for growth and poverty reduction. *World Development*, 38(10): 1429–1441. https://doi.org/10.1016/j.worlddev.2009.06.008

HarvestChoice & IFPRI (International Food Policy Research Institute). 2018. Travel Time to Markets in Africa South of the Sahara. In: *Harvard Dataverse, V*2, Boston. Cited 19 November 2021. https://doi.org/10.7910/DVN/YKDWJD

Heckman, J.J. & Robb Jr, R. 1985. Alternative methods for evaluating the impact of interventions: An overview. *Journal of econometrics*, 30(1-2): 239–267. https://doi.org/10.1016/0304-4076(85)90139-3

Huber, M., Lechner, M. & Mellace, G. 2017. Why do tougher caseworkers increase employment? The role of program assignment as a causal mechanism. *Review of Economics and Statistics*, 99(1): 180–183. https://doi.org/10.1162/REST_a_00632

Imai, K., Keele, L. & Tingley, D. 2010. A general approach to causal mediation analysis. *Psychological Methods*, 15(4): 309–334. https://doi.org/10.1037/a0020761

Imai, K., Keele, L., Tingley, D. & Yamamoto, T. 2011. Unpacking the black box of causality: Learning about causal mechanisms from experimental and observational studies. *American Political Science Review*, 105(4): 765–789. https://doi.org/10.1017/S0003055411000414

Imbens, G.W. & Wooldridge, J.M. 2009. Recent developments in the econometrics of program evaluation. *Journal of Economic Literature*, 47(1): 5–86. https://doi.org/10.1257/ jel.47.1.5

Leng, C., Ma, W., Tang, J., & Zhu, Z. 2020. ICT adoption and income diversification among rural households in China. *Applied Economics*, 52(33): 3614–3628. https://doi.org/10.1080/00036846.2020.1715338

Lobell, D.B., Azzari, G., Burke, M., Gourlay, S., Jin, Z., Kilic, T. & Murray, S. 2020. Eyes in the Sky, Boots on the Ground: Assessing Satellite-and Ground-Based Approaches to Crop Yield Measurement and Analysis. *American Journal of Agricultural Economics*, 102(1): 202–219. https://doi.org/10.1093/ajae/aaz051

Mekonnen, D.K., Abate, G.T., Yimam, S., Benfica, R., Spielman, D.J. & Place, F. 2021. *The impact of Ethiopia's direct seed marketing approach on smallholders' access to seeds, productivity, and commercialization.* IFPRI.

Min, S., Liu, M., & Huang, J. 2020. Does the application of ICTs facilitate rural economic transformation in China? Empirical evidence from the use of smartphones among farmers. *Journal of Asian Economics*, 70: 101219. https://doi.org/10.1016/j.asieco.2020.101219

Minnesota Population Center. 2020. Integrated Public Use Microdata Series, International: Version 7.3, The 2007 Population and Housing Census of Ethiopia. In: *IPUMS*, Minneapolis. Cited 19 November 2021. https://doi.org/10.18128/D020.V7.2

Morgan, S.L. & Winship, C. 2015. *Counterfactuals and Causal Inference.* Cambridge University Press.

Moriondo, M., Maselli, F. & Bindi, M. 2007. A simple model of regional wheat yield based on NDVI data. *European Journal of Agronomy*, 26(3): 266–274. https://doi.org/10.1016/j.eja.2006.10.007

Owusu, V., Abdulai, A. & Abdul-Rahman, S. 2011. Non-farm work and food security among farm households in Northern Ghana. *Food Policy*, 36(2): 108–118. https://doi.org/10.1016/j.foodpol.2010.09.002

Pace, N., Sebastian, A., Daidone, S., Prifti, E. & Davis, B. 2022. Mediation analysis of the impact of the Zimbabwe Harmonized Social Cash Transfer Programme on food security and nutrition. *Food Policy*, 106: 102190. https://doi.org/10.1016/j.foodpol.2021.102190

Pan, Y., Smith, S. C. & Sulaiman, M. 2018. Agricultural extension and technology adoption for food security: Evidence from Uganda. *American Journal of Agricultural Economics*, 100(4): 1012–1031. https://doi.org/10.1093/ajae/aay012

Panek, E. & Gozdowski, D. 2020**.** Analysis of relationship between cereal yield and NDVI for selected regions of Central Europe based on MODIS satellite data. *Remote Sensing Applications: Society and Environment,* 17, 100286. https://doi.org/10.1016/j.rsase.2019.100286.

PDC (Planning and Development Commission). 2021. *Development Plan: A Pathway to Prosperity, 2021 – 2030.*

Powdthavee, N., Lekfuangfu, W.N. & Wooden, M. 2013. *The marginal income effect of education on happiness: Estimating the direct and indirect effects of compulsory schooling on well-being in Australia.* https://docs.iza.org/dp7365.pdf

Rahman, A. & Mishra, S. 2020. Does non-farm income affect food security? Evidence from India. *The Journal of Development Studies*, 56(6): 1190–1209. https://doi.org/10.1080/00220388.2019.1640871

Reardon, T., Delgado, C. & Matlon, P. 1992. Determinants and effects of income diversification amongst farm households in Burkina Faso. *The Journal of Development Studies*, 28(2): 264–296. https://doi.org/10.1080/00220389208422232

Rosenbaum, P.R. & Rubin, D.B. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1): 41–55. https://doi.org/10.1093/ biomet/70.1.41

Salazar, L., Aramburu, J., González-Flores, M. & Winters, P. 2015. Food security and productivity: impacts of technology adoption in small subsistence farmers in Bolivia. *IDB working paper series No. IDB-WP-567.* http://hdl.handle.net/10419/115514

Salazar, L., Palacios, A., Selvaraj, M. & Montenegro, F. 2021. *Using Satellite Images to Measure Crop Productivity: Long-Term Impact Assessment of a Randomized Technology Adoption Program in the Dominican Republic*.

Sultana, S.R., Ali, A., Ahmad, A., Mubeen, M., Zia-Ul-Haq, M., Ahmad, S., Ercisli, S. & Jaafar, H.Z. 2014. Normalized difference vegetation index as a tool for wheat yield estimation: a case study from Faisalabad, Pakistan. *The Scientific World Journal*, 2014: 725326. https://doi.org/10.1155/2014/725326

Sun, L. & Abraham, S. 2020. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2): 175–199. https://doi.org/10.1016/j.jeconom.2020.09.006

Tsiboe, F., Zereyesus, Y.A. & Osei, E. 2016. Non-farm work, food poverty, and nutrient availability in northern Ghana. *Journal of Rural Studies*; 47: 97–107. https://doi.org/10.1016/j.jrurstud.2016.07.027

USGS (United States Geological Survey). 2021. Landsat-7 Surface Reflectance 1999-Present. In: *U.S. Geological Survey*, Reston. Cited 19 November 2021. https://www.usgs.gov/landsat-missions/landsat-collection-1-surface-reflectance.

Webb, P. & Reardon, T. 1992. Drought impact and household response in East and West Africa. *Quarterly Journal of International Agriculture*, 31: 230–230.

Wooldridge, J. M. 2015. Control function methods in applied econometrics. *Journal of Human Resources*, 50(2): 420–445. https://doi.org/10.3368/jhr.50.2.420

World Bank. 2019a. *World Development Indicators: Employment in agriculture (% of total employment) (modeled ILO estimates) – Ethiopia.* Cited 19 November 2021. https://data.worldbank.org/indicator/ SL.AGR.EMPL.ZS?locations=ET

World Bank. 2019b. *World Development Indicators: Prevalence of moderate or severe food insecurity in the population (%) – Ethiopia*. Cited 19 November 2021. https://data.worldbank.org/indicator/ SN.ITK.MSFI.ZS?locations=ET

World Bank. 2019c. *World Development Indicators: Prevalence of anemia among women of reproductive age (% of women ages 15-49) – Ethiopia*. Cited 19 November 2021. https://data.worldbank.org/indicator/ SH.ANM.ALLW.ZS?locations=ET

World Bank. 2019d. *World Development Indicators: Prevalence of stunting, height for age (% of children under 5) – Ethiopia*. Cited 19 November 2021. https://data.worldbank.org/indicator/SH.STA.STNT.ZS? locations=ET

WorldPop. 2021. Global Project Population Data. In: *WorldPop*, Southampton. Cited 19 November 2021. www.worldpop.org.

Zereyesus, Y.A., Embaye, W.T., Tsiboe, F. & Amanor-Boadu, V. 2017. Implications of non-farm work to vulnerability to food poverty-recent evidence from Northern Ghana. *World Development*, 91: 113–124. https://doi.org/10.1016/j.worlddev.2016.10.015

Annex

Table A1. Evolution of treatment status for rural households in the ESS panel

		2011/2012	2013/2014	2015/2016
Households	Control	3 466	3 036	1 923
	Treated	0	287	1 299
	Total	3 466	3 323	3 222
Districts	Control	239	214	131
	Treated	0	25	107
	Total	239	239	238

Source: Authors' own elaboration.

Table A2. Correlation between NDVI and agricultural yields

	All crops			Cereals		
	1	2	3	1	2	3
NDVI	0.880*	3.326***	4.678***	1.532***	4.242***	5.611***
	(0.483)	(1.025)	(1.238)	(0.552)	(1.368)	(1.547)
District fixed effects		YES	YES		YES	YES
Year fixed effects			YES			YES
Adjusted R2	0.01	0.04	0.09	0.03	0.05	0.01
Yields mean in 2013	850	850	850	775	775	850
Yields mean in 2015	670	670	670	657	657	670
Districts	276	276	276	263	263	276
Observations	524	524	524	501	501	524

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors clustered at the district level reported in parentheses. Coefficients reported are semi-elasticities obtained using the methodology proposed by Bellemare and Wichman (2020). As recommended by Bellemare and Wichman (2020), NDVI and yields variables are multiplied by a factor of ten to obtained more stable estimates.

Source: Authors' own elaboration.

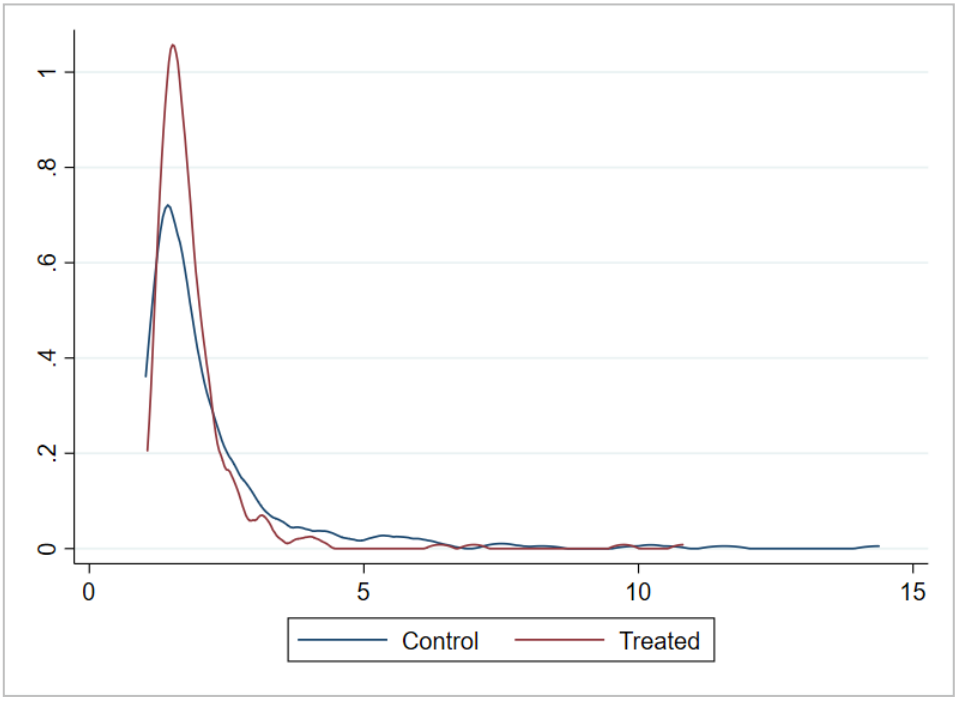
Table A3. Descriptive statistics of main household outcomes

	2011/2012		2013/2014		2015/2016	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Food security						
Food gap in past 12 months (0/1)	0.33	0.47	0.35	0.48	0.31	0.46
Months of food gap	2.90	1.55	3.00	1.56	3.37	2.23
Household dietary diversity score	4.94	1.61	5.17	1.59	5.42	1.57
Food consumption score	43.39	17.22	45.50	16.86	46.09	15.98
Total food consumption (Birr)	2 601	3 343	2 099	1 585	1 961	1 465
Labour strategies						
No labour activity (0/1)	0.08	0.26	0.07	0.25	0.11	0.31
On-farm specialization (0/1)	0.55	0.50	0.42	0.49	0.53	0.50
Survival-led off-farm (0/1)	0.17	0.38	0.29	0.46	0.17	0.37
Opportunity-led off-farm (0/1)	0.20	0.40	0.22	0.41	0.19	0.40
Migration						
Any migration (0/1)	0.06	0.23	0.39	0.49	0.55	0.50
Households	3 466		3 323			3 222

Note: Months of food gap is conditional on having experienced food gap in past 12 months.

Source: Authors' own elaboration.

Figure A1. Distribution of inverse-probability weights



Source: Authors' own elaboration.

Table A4. Impact on NDVI – full specification

	1 June to August	2 June to September	3 June to October	4 June to November	5 June to December
Treated	0.005**	0.004*	0.005***	0.004**	0.004***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Rainfall anomaly	0.003***	0.003***	0.003***	0.007***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Population	0.003	0.002	0.001	0.001	0.001
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Constant	0.510***	0.530***	0.550***	0.544***	0.533***
	(0.006)	(0.005)	(0.002)	(0.002)	(0.002)
District fixed effects	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES
Adjusted R2	0.25	0.26	0.17	0.13	0.13
Control mean in 2011	0.51	0.53	0.55	0.55	0.55
Control mean in 2016	0.53	0.54	0.55	0.55	0.54
Districts	624	624	624	624	624
Observations	3 744	3 744	3 744	3 744	3 744

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Models correct for inverse probability weighting adjustment. Rainfall anomaly is measured over the same period as NDVI. Addis Ababa region excluded.

Source: Authors' own elaboration.

Table A5. Impact on NDVI – callaway and Sant'Anna (2021) estimator

	1 June to August	2 June to September	3 June to October	4 June to November	5 June to December
Treated	0.005	0.004	0.006***	0.005***	0.005***
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
District fixed effects	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES
Covariates	YES	YES	YES	YES	YES
Control mean in 2011	0.51	0.53	0.55	0.55	0.55
Control mean in 2016	0.53	0.54	0.55	0.55	0.54
Observations	3 744	3 744	3 710	3 710	3 710

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Models correct for inverse probability weighting adjustment and control for population and rainfall anomaly (measured over the same period than NDVI). Addis Ababa region excluded.

Source: Authors' own elaboration.

Table A6. Impact on food security – full specification

	1 Food gap	2 Months of food gap	3 Household Dietary Diversity	4 Food Consumption Score	5 Total food consumption
Treated	-0.066*	-0.680**	0.085	2.662**	0.159***
	(0.036)	(0.342)	(0.117)	(1.216)	(0.050)
Head covariates					
Female	0.020	0.386	-0.039	-0.045	0.036
	(0.029)	(0.548)	(0.140)	(1.079)	(0.068)
Age	0.001	0.008	0.008**	0.095**	0.003
	(0.001)	(0.016)	(0.004)	(0.042)	(0.002)
Married	0.001	-0.095	0.041	-0.310	-0.003
	(0.032)	(0.351)	(0.114)	(0.911)	(0.046)
Household covariates					
Household size	0.014	0.126	0.110***	1.124***	-0.035**
	(0.009)	(0.108)	(0.036)	(0.296)	(0.014)
Number of active age members	-0.002	-0.138	-0.023	-0.052	-0.050***
	(0.008)	(0.152)	(0.040)	(0.299)	(0.016)
Maximum educational attainment of active age members	-0.007*	0.006	0.015	0.082	-0.006
	(0.003)	(0.035)	(0.009)	(0.091)	(0.004)
Agricultural wealth index	-0.070	-0.117	0.777*	7.095	0.397**
	(0.122)	(1.598)	(0.414)	(4.460)	(0.162)
Non-agricultural wealth index	-0.180*	0.116	0.752**	0.205	-0.197
	(0.097)	(2.005)	(0.346)	(3.204)	(0.372)
Credit	0.076***	-0.101	0.137**	0.705	0.009
	(0.023)	(0.266)	(0.060)	(0.608)	(0.023)
Community covariates					
Price index	-0.001	-0.008	-0.004	0.054	0.002
	(0.002)	(0.016)	(0.006)	(0.048)	(0.003)
Accessible by vehicle	-0.031	-0.337	-0.006	0.968	-0.041
	(0.039)	(0.278)	(0.099)	(0.808)	(0.035)
Market	0.019	0.165	-0.093	-2.298**	-0.019
	(0.035)	(0.175)	(0.090)	(0.919)	(0.036)
Health post	0.028	0.626	-0.140	0.196	0.026
	(0.036)	(0.509)	(0.151)	(1.248)	(0.047)
Financial institution	-0.074*	-0.552**	-0.141	-0.371	0.040
	(0.039)	(0.245)	(0.090)	(0.967)	(0.043)
Job cooperative	0.080	-0.133	-0.026	-0.298	-0.052
	(0.056)	(0.353)	(0.164)	(1.540)	(0.042)

	1 Food gap	2 Months of food gap	3 Household Dietary Diversity	4 Food Consumption Score	5 Total food consumption
PSNP	-0.079	0.215	0.073	-0.163	-0.079
	(0.077)	(0.570)	(0.193)	(2.070)	(0.075)
Rainfall anomaly	0.015	-0.232	-0.001	-0.267	-0.008
	(0.019)	(0.182)	(0.056)	(0.540)	(0.026)
Constant	0.218**	1.986	4.090***	30.807***	7.795***
	(0.085)	(1.361)	(0.300)	(3.212)	(0.161)
Household fixed effects	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES
Adjusted R2	0.03	0.05	0.04	0.02	0.06
Control mean in 2011/12	0.31	2.96	4.88	42.33	7.65
Control mean in 2015/16	0.36	3.63	5.33	43.40	7.32
Districts	230	219	230	230	230
Households	3 212	1 771	3 213	3 213	3 208
Observations	9 176	2 886	9 208	9 208	8 866

Notes: * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors clustered at the district level reported in parentheses. Models correct for inverse probability weighting adjustment. "Months of food gap" is conditional on having experienced food gap in past 12 months. "Total food consumption" is expressed in log. Rainfall anomaly is measured over the June to October period.

Source: Authors' own elaboration.

Table A7. Impact on food security – callaway and Sant'Anna (2021) estimator

	1 Food gap	2 Months of food gap	3 Household Dietary Diversity	4 Food Consumption Score	5 Total food consumption
Treated	-0.038	-0.088	0.120	2.831**	0.165***
	(0.044)	(0.455)	(0.129)	(1.321)	(0.053)
Household fixed effects	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES
Covariates	YES	YES	YES	YES	YES
Control mean in 2011/12	0.31	2.96	4.88	42.33	0.31
Control mean in 2015/16	0.36	3.63	5.33	43.40	0.36
Observations	9 020	1 742	9 065	9 065	9 020

Notes: * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors clustered at the district level reported in parentheses. Models correct for inverse probability weighting adjustment. Covariates include those described in Section 4.3. "Months of food gap" is conditional on having experienced food gap in past 12 months. "Total food consumption" is expressed in log.

Source: Authors' own elaboration.

Table A8. Impact on labour strategies – full specification

	1 No labour activity	2 On-farm specialization	3 Survival-led off-farm	4 Opportunity-led off-farm
Treated	0.006	-0.058*	0.008	0.045**
	(0.015)	(0.035)	(0.031)	(0.022)
Head covariates				
Female	0.025	0.036	-0.019	-0.042*
	(0.022)	(0.029)	(0.030)	(0.024)
Age	-0.001	0.003**	0.001	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Married	-0.006	0.039	-0.022	-0.011
	(0.017)	(0.028)	(0.020)	(0.019)
Household covariates				
Household size	-0.015***	0.010	-0.002	0.008
	(0.006)	(0.009)	(0.008)	(0.008)
Number of active age members	-0.009	-0.009	0.019**	-0.000
	(0.006)	(0.012)	(0.008)	(0.007)
Maximum educational attainment of active age members	-0.004*	0.001	0.003	0.000
	(0.002)	(0.004)	(0.003)	(0.002)
Agricultural wealth index	-0.099**	-0.040	0.139	-0.000
	(0.046)	(0.103)	(0.099)	(0.090)
Non-agricultural wealth index	-0.103***	-0.059	-0.064	0.227**
	(0.038)	(0.089)	(0.066)	(0.092)
Credit	-0.011	-0.068***	0.034**	0.045***
	(0.008)	(0.016)	(0.015)	(0.015)
Community covariates				
Price index	0.001	0.001	-0.003	0.001
	(0.001)	(0.001)	(0.002)	(0.001)
Accessible by vehicle	0.014	-0.018	-0.010	0.014
	(0.012)	(0.023)	(0.022)	(0.014)
Market	-0.009	-0.021	0.028	0.002
	(0.013)	(0.020)	(0.019)	(0.014)
Health post	-0.002	-0.022	0.040	-0.016
	(0.017)	(0.041)	(0.038)	(0.022)
Financial institution	0.037***	0.005	0.003	-0.045***
	(0.013)	(0.034)	(0.029)	(0.016)
Job cooperative	-0.030**	-0.035	0.051	0.014
	(0.015)	(0.033)	(0.039)	(0.024)
PSNP	0.010	-0.063	0.027	0.026
	(0.019)	(0.040)	(0.036)	(0.026)

	1 No labour activity	2 On-farm specialization	3 Survival-led off-farm	4 Opportunity-led off-farm
Rainfall anomaly	0.005	-0.020	0.019	-0.004
	(0.008)	(0.021)	(0.019)	(0.009)
Constant	0.236***	0.397***	0.012	0.356***
	(0.047)	(0.095)	(0.074)	(0.086)
Household fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Adjusted R2	0.02	0.03	0.03	0.01
Control mean in 2011/12	0.07	0.49	0.13	0.31
Control mean in 2015/16	0.11	0.50	0.12	0.27
Districts	230	230	230	230
Households	3 213	3 213	3 213	3 213
Observations	9 208	9 208	9 208	9 208

Notes: * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors clustered at the district level reported in parentheses. Models correct for inverse probability weighting adjustment. Rainfall anomaly is measured over the June to October period.

Source: Authors' own elaboration.

Table A9. Impact on labour strategies – callaway and Sant'Anna (2021) estimator

	1 No labour activity	2 On-farm specialization	3 Survival-led off-farm	4 Opportunity-led off-farm
Treated	-0.006	0.015	-0.049	0.039*
	(0.019)	(0.039)	(0.038)	(0.024)
Household fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Covariates	YES	YES	YES	YES
Control mean in 2011/12	0.07	0.48	0.18	0.26
Control mean in 2015/16	0.11	0.50	0.17	0.22
Observations	9 065	9 065	9 065	9 065

Notes: * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors clustered at the district level reported in parentheses. Models correct for inverse probability weighting adjustment. Covariates include those described in Section 4.3.

Source: Authors' own elaboration.

Table A10. Impact on migration – full specification

	1 **Any migration** All waves	2 **Any migration** Excluding wave 1
Treated	0.050**	0.026
	(0.019)	(0.020)
Head covariates		
Female	0.059	0.127*
	(0.046)	(0.071)
Age	0.000	0.002
	(0.001)	(0.002)
Married	-0.067***	-0.054
	(0.025)	(0.040)
Household covariates		
Household size	0.076***	0.056***
	(0.008)	(0.014)
Number of active age members	-0.073***	-0.059***
	(0.011)	(0.016)
Maximum educational attainment of active age members	-0.020***	-0.027***
	(0.003)	(0.006)
Agricultural wealth index	0.087	-0.210*
	(0.096)	(0.107)
Non-agricultural wealth index	0.046	-0.088
	(0.073)	(0.174)
Credit	0.004	-0.003
	(0.015)	(0.023)
Community covariates		
Price index	0.000	0.000
	(0.001)	(0.001)
Accessible by vehicle	0.007	-0.031
	(0.018)	(0.022)
Market	0.021	0.003
	(0.013)	(0.021)
Health post	-0.044	0.005
	(0.047)	(0.023)
Financial institution	0.050**	-0.004
	(0.023)	(0.028)
Job cooperative	-0.007	0.027
	(0.022)	(0.033)
PSNP	0.030	0.041
	(0.030)	(0.035)

	1 **Any migration** All waves	2 **Any migration** Excluding wave 1
Rainfall anomaly	0.011	0.009
	(0.014)	(0.012)
Constant	-0.069	0.254**
	(0.093)	(0.120)
Household fixed effects	YES	YES
Year fixed effects	YES	YES
Adjusted R2	0.32	0.15
Control mean in 2011/12	0.05	
Control mean in 2013/14	0.31	0.31
Control mean in 2015/16	0.45	0.45
Districts	230	206
Households	3 213	2 812
Observations	9 208	5 503

Notes: * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors clustered at the district level reported in parentheses. Models correct for inverse probability weighting adjustment. Rainfall anomaly is measured over the June to October period. Column 2 restricts to wave 2 and 3, while ignoring households treated in wave 2.

Source: Authors' own elaboration.

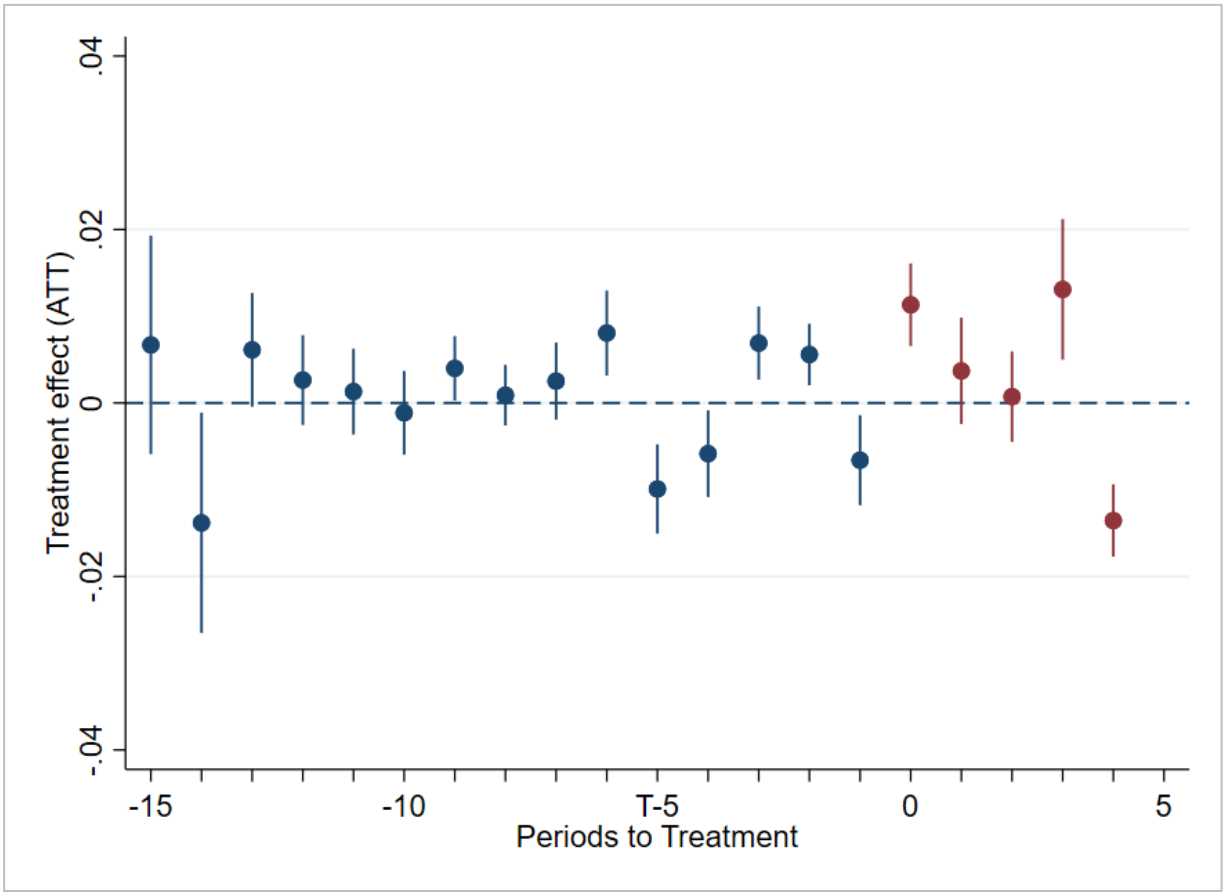
Table A11. Impact on migration – callaway and Sant'Anna (2021) estimator

	1 **Any migration** All waves
Treated	0.035
	(0.026)
Household fixed effects	YES
Year fixed effects	YES
Covariates	YES
Control mean in 2011/12	0.05
Control mean in 2013/14	0.31
Control mean in 2015/16	0.45
Observations	9 065

Notes: * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors clustered at the district level reported in parentheses. Models correct for inverse probability weighting adjustment. Covariates include those described in Section 4.3.

Source: Authors' own elaboration.

Figure A2. Checking parallel trends assumption for NDVI (main growing period)

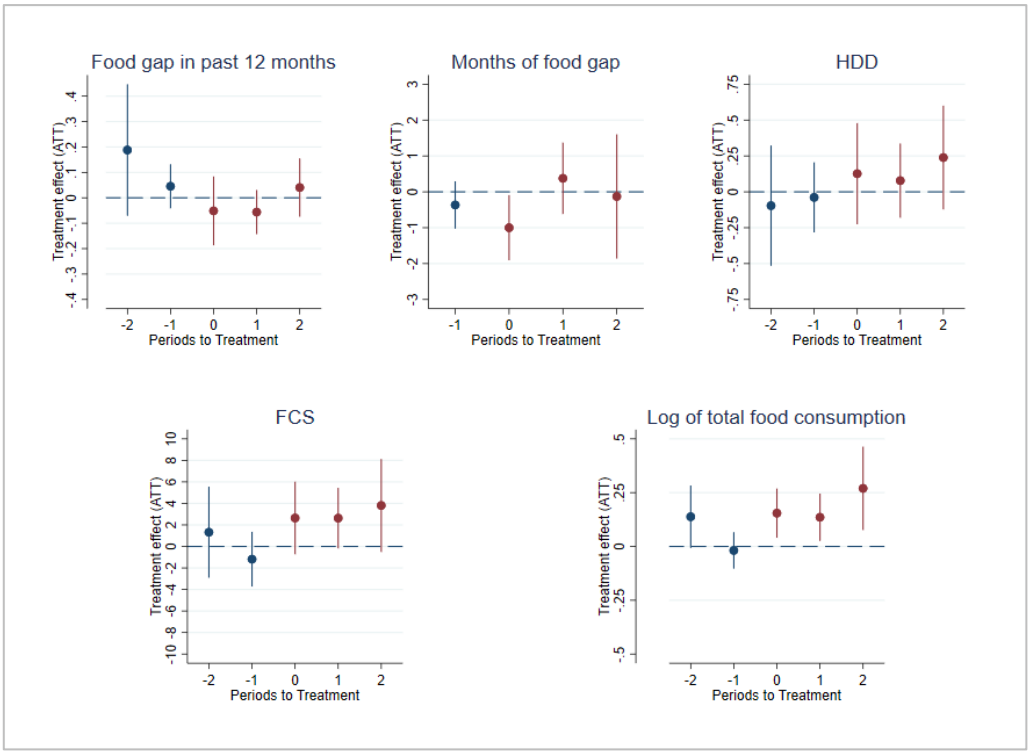


Notes: Bars represent 90 percent confidence intervals. NDVI is computed over the months of the main growing period (June to October). The coefficient for T+0 is estimated on 327 treated districts, the coefficient for T+1 is estimated on 260 treated districts, the coefficient for T+2 is estimated on 226 treated districts, the coefficient for T+3 is estimated on 58 treated districts and the coefficient for T+4 is estimated on one treated district.

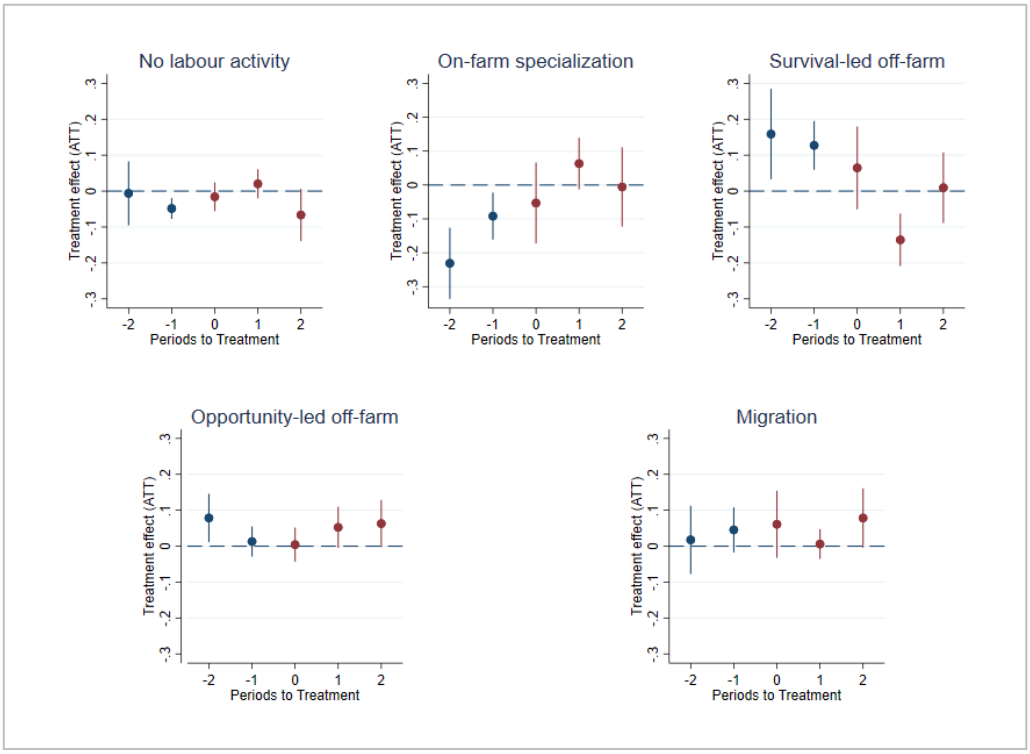
Source: Authors' own elaboration.

Figure A3. Checking parallel trends assumption for food security and livelihood strategies

a. Parallel trends for food security outcomes



b. Parallel trends for livelihood strategies

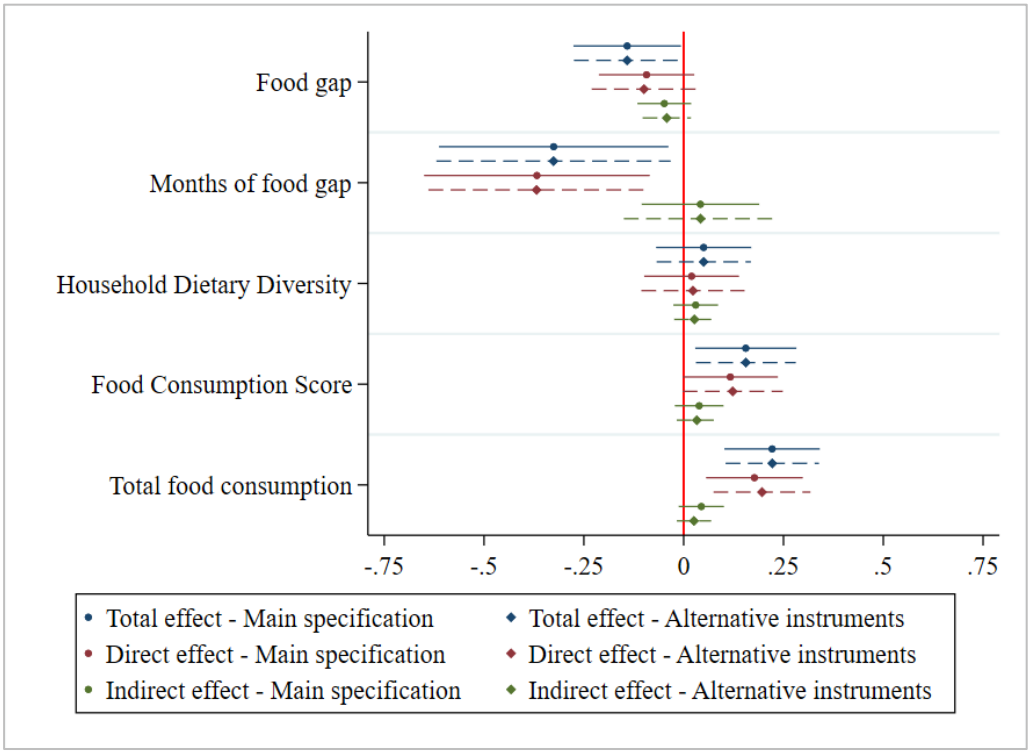


Note: Bars represent 90 percent confidence intervals.

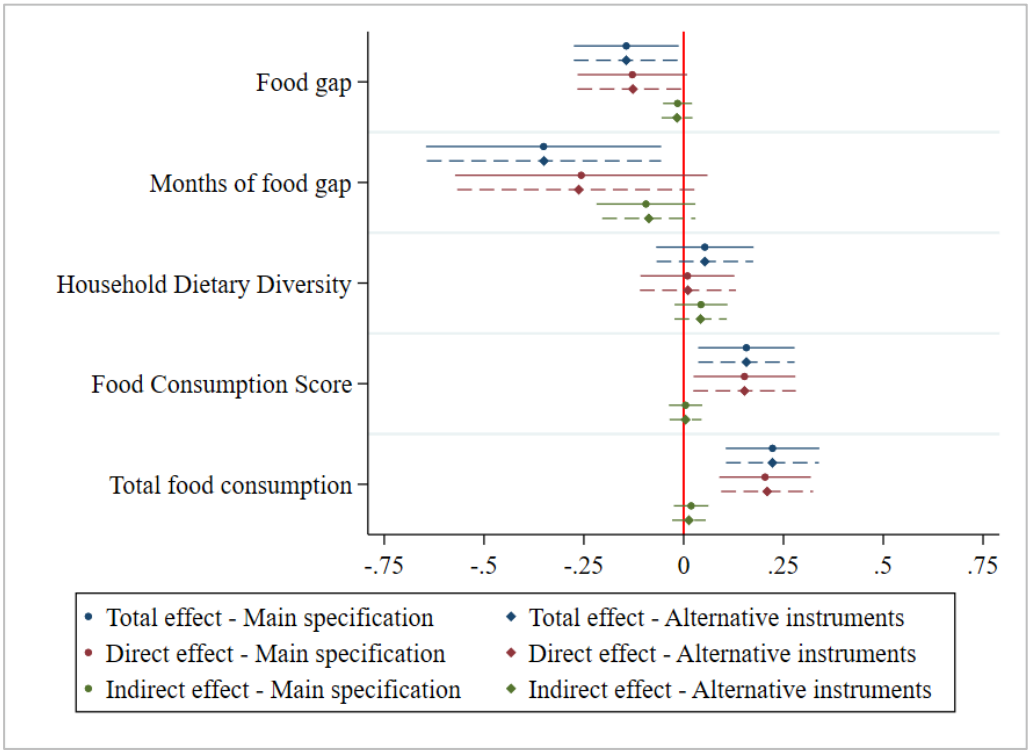
Source: Authors' own elaboration.

Figure A4. Checking mediation results across alternative specifications

a. Opportunity-led off-farm as mediator variable



b. Any migration as mediator variable



Notes: Standardized coefficients reported. Bars represent 90 percent confidence intervals. Alternative instruments include the instruments of the main specification as well as an indicator for rural households reporting access to electricity and the interaction between this indicator and the indicator for rural households living in a community with a job cooperative.

Source: Authors' own elaboration.

Table A12. Instrumenting the mediator variables

	Main specification		Alternative instruments	
	1 Opportunity-led off-farm	2 Any migration	3 Opportunity-led off-farm	4 Any migration
Treated	0.043**	0.052***	0.043**	0.052***
	(0.021)	(0.020)	(0.021)	(0.020)
Job cooperative	-0.018	-0.045	-0.029	-0.048*
	(0.028)	(0.028)	(0.029)	(0.028)
Secondary education	-0.028	-0.114***	-0.026	-0.113***
	(0.033)	(0.027)	(0.032)	(0.027)
Job cooperative x secondary education	0.088*	-0.025	0.075	-0.029
	(0.052)	(0.038)	(0.048)	(0.040)
Mobile phone	0.046**	-0.015	0.049***	-0.014
	(0.019)	(0.017)	(0.018)	(0.017)
Job cooperative x mobile phone	0.042	0.103**	0.024	0.099**
	(0.037)	(0.042)	(0.042)	(0.045)
Electricity			-0.033	-0.013
			(0.022)	(0.027)
Job cooperative x electricity			0.083**	0.024
			(0.038)	(0.045)
Household fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Covariates	YES	YES	YES	YES
F-stat excluded instruments	3.60	6.24	5.13	5.70
p-value excluded instruments	0.00	0.00	0.00	0.00
Adjusted R2	0.02	0.32	0.02	0.32
Control mean in 2011/12	0.31	0.05	0.31	0.05
Control mean in 2015/16	0.27	0.45	0.27	0.45
Districts	230	230	230	230
Households	3 213	3 213	3 213	3 213
Observations	9 208	9 208	9 207	9 207

Notes: * p<0.1, ** p<0.05, *** p<0.01. Robust standard errors clustered at the district level reported in parentheses. Models correct for inverse probability weighting adjustment. Covariates include those described in Section 4.3.

Source: Authors' own elaboration.

Table A13. Checking SUTVA assumption on NDVI for the main growing period

	1 All districts	2 Excluding control districts adjacent to treated districts
Treated	0.005***	0.005**
	(0.002)	(0.002)
District fixed effects	YES	YES
Year fixed effects	YES	YES
Controls	YES	YES
Adjusted R2	0.17	0.14
Control mean in 2011	0.55	0.54
Control mean in 2016	0.55	0.55
Districts	624	471
Observations	3 744	2 826

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. NDVI is computed over the months of the main growing period (June to October). Models correct for inverse probability weighting adjustment and control for population and rainfall anomaly (for the main growing period). Addis Ababa region excluded.

Source: Authors' own elaboration.

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CONTACTS

Agrifood Economics Division – Economic and Social Development
ESA-Director@fao.org
www.fao.org/agrifood-economics

Food and Agriculture Organization of the United Nations
Rome, Italy

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