INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

IFPRI

IFPRI Discussion Paper 02114

April 2022

Roles of Public Expenditures and Public Investments on the Demand and Productivity of Agricultural Inputs/Services

Some Insights from Nigeria

Hiroyuki Takeshima

Hyacinth Edeh

Kwaw Andam

Development Strategy and Governance Division

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

The International Food Policy Research Institute (IFPRI), a CGIAR Research Center established in 1975, provides research-based policy solutions to sustainably reduce poverty and end hunger and malnutrition. IFPRI's strategic research aims to foster a climate-resilient and sustainable food supply; promote healthy diets and nutrition for all; build inclusive and efficient markets, trade systems, and food industries; transform agricultural and rural economies; and strengthen institutions and governance. Gender is integrated in all the Institute's work. Partnerships, communications, capacity strengthening, and data and knowledge management are essential components to translate IFPRI's research from action to impact. The Institute's regional and country programs play a critical role in responding to demand for food policy research and in delivering holistic support for country-led development. IFPRI collaborates with partners around the world.

AUTHORS

Hiroyuki Takeshima (H.takeshima@cgiar.org) is a Senior Research Fellow in the Development Strategy and Governance Division of the International Food Policy Research Institute (IFPRI), Washington, DC.

Hyacinth Edeh (H.edeh@cgiar.org) is a Country Program Manager in IFPRI's Development Strategy and Governance Division, Abuja, Nigeria.

Kwaw Andam (K.andam@cgiar.org) is a Country Program Leader / Research Fellow in IFPRI's Development Strategy and Governance Division, Abuja, Nigeria.

Notices

[1] IFPRI Discussion Papers contain preliminary material and research results and are circulated in order to stimulate discussion and critical comment. They have not been subject to a formal external review via IFPRI's Publications Review Committee. Any opinions stated herein are those of the author(s) and are not necessarily representative of or endorsed by IFPRI.

[2] The boundaries and names shown and the designations used on the map(s) herein do not imply official endorsement or acceptance by the International Food Policy Research Institute (IFPRI) or its partners and contributors.

Abstract

Knowledge gaps remain as to how longer-term public investments (PI) such as agricultural research and development (R&D), and short-term interventions through other public expenditures in agriculture (PEA) complement each other in enhancing productivity and efficiency in the agrifood sector. This study attempts to partly fill this gap by using nationally representative panel household survey data, subnational PEA data, locations of national agricultural R&D, and various spatial agroclimatic data in Nigeria. The analyses generally indicate that marginal returns to agricultural inputs/services (fertilizer, agricultural mechanization, irrigation, extension, agricultural equipment, and family labor) often increase by PI that raise overall agroclimatic similarity (AS) (through R&D locations), as well as increase PEA-share by subnational governments. There is often complementarity between these PI and PEA, particularly for extension services, investment in agricultural equipment, irrigation, and in the northern part of the country. Promoting further adoptions of modern inputs/services, increasing PEA-share, and selecting PI for agricultural R&D given in-country variations in agroclimatic conditions can help raise agricultural profitability and incomes in Nigeria.

Keywords: public investment, public expenditure, agricultural inputs and services, productivity, stratified difference-in-difference propensity-score matching, Nigeria

Acknowledgments

This paper has been prepared as an output of the Nigeria Strategy Support Program, which has been managed by the International Food Policy Research Institute (IFPRI) and has been financially made possible by the generous support of the American people through the United States Agency for International Development (USAID) in connection with the Feed the Future Nigeria Agricultural Policy Project. This paper has not undergone IFPRI's standard peer-review procedure. The opinions expressed here belong to the authors and do not necessarily reflect those of USAID, IFPRI, or the CGIAR. The authors are responsible for all remaining errors.

1 Introduction

Public investments (PI), public expenditures for agriculture (PEA) have been recognized as important tools for agrifood system transformation globally (Mogues & Benin 2012; Takeshima et al. 2021). Higher productivity and economic returns to inputs/services have been one of the primary drivers of PI and PEA adoptions, including improved seeds (Michler et al. 2019), chemical fertilizer (Dadi et al. 2004), mechanization (Takeshima et al. 2015; Takeshima & Liu 2020), and irrigation (Otsuka & Larson 2012). Here, the effects of this linkage on agricultural inputs/services include not only reducing costs/raising accessibility but also raising the productivity/returns to these inputs/services. Similarly, raised efficiency of inputs/services offers ways to achieve sustainable growth in resource-conserving ways. Furthermore, raising productivity/returns to certain inputs like labor directly contributes to rural per capita income growth, enabling agrifood system transformation to also contribute to rural poverty reduction and equitable growth.

Literature has long recognized that returns to agricultural inputs/services can be heterogeneous and vary across locations (e.g., Feder & Umali 1993; Evenson & Westphal 1995). However, spatial variations in PI/PEA can also generate exogenous sources of such spatial variations. Understanding how spatial variations in PI/PEA affect spatial variations in the returns to agricultural inputs/services is important for optimally designing PI/PEA policies.[1]

In particular, a potentially important question is the interaction between PI, including investment in agricultural R&D (which often focus on developing technologies including improved varieties over the long-term), and PEA that affects the farm economic environments in a more short-term (for example, through effects on the prices of inputs/services and outputs, access to goods and markets, among others).[2] Agricultural R&D locations can affect spillover potentials of R&D-developed technologies, and they depend on the agroclimatic similarity (AS), which can generally be defined as the similarity in agroclimatic conditions between locations where agricultural R&D are conducted to develop technologies, and farm locations where those technologies are actually used (e.g., Alston 2002; Evenson & Gollin 2003; Takeshima 2019). Optimal PI/PEA policies can depend on whether subnational PEA by states or Local Government Areas (LGA) raises returns to inputs/services in their locality and whether these effects of PEA are higher in areas that are agroclimatically similar to agricultural R&D locations

---

[1]Heterogeneity of returns and productivity have also been recognized for specific inputs/services, including fertilizer, extension services, irrigation, and mechanization. For example, returns to chemical fertilizer are found to vary between lowland and upland in Nepal (Takeshima et al. 2017), and crop response to fertilizer can differ widely with geographic location, depending on agroclimatic conditions like soil quality (Burke et al. 2019; Rurinda et al. 2020). Similarly, heterogeneous productivity/returns in developing countries like Nigeria have been reported for extension services (Coelli et al. 2003; Fuwa et al. 2007; Davis et al. 2020), labor (e.g., O'Gorman & Pandey 2010), irrigation (Comas et al. 2012; Takeshima & Yamauchi 2012; Xie et al. 2017; Njuki & Bravo-Ureta 2019), and mechanization (Takeshima et al. 2013; Takeshima & Liu 2020).

A few of these studies specifically identify that returns and adoptions are particularly higher in areas where improved technologies developed from agricultural R&D have been more widely adopted. Where the production frontier has been raised through improved technologies, for example, there is greater scope for extension services to narrow the efficiency gap (Coelli et al., 2003; Fuwa et al., 2007). Similarly, high-yielding seed explains 22% of variations in agricultural labor productivity across countries (O'Gorman & Pandey 2010 JDS), while returns to and adoptions of mechanization in Ghana have been higher in areas where yield potential has been raised through spillover of improved varieties developed through agricultural R&D (Takeshima & Liu 2020).

[2]We distinguish between agricultural R&D and PEA, even though PEA is still the source of recurrent and capital expenditures for agricultural R&D. This is because agricultural R&D tends to be longer-term activities, of which outputs depend on cumulative inflow from PEA over many years (and thus closer to PI in nature), while PEA in a particular year tends to be used for more short-term purposes.

(where spillover potentials of R&D-developed technologies are higher). For example, if there is complementarity between PEA and AS with agricultural R&D locations, overall returns to PEA can be enhanced by targeting areas with higher AS or by expanding R&D locations in ways that raise AS for more farmers in the country.

Knowledge gaps about the complementarity between PI and PEA in developing countries like Nigeria remain. This study, therefore, partly fills this gap through household-level evidence from Nigeria. Specifically, we assess how subnational PEAs affect the productivity of various key agricultural inputs/services at farm household levels and how these impacts vary across locations depending on the spillover potentials of technologies developed by PI in agriculture (agricultural R&D). We combine household-level data from the Living Standard Measurement Study-Integrated Survey on Agriculture (LSMS-ISA), as well as data on PEA from the Government of Nigeria (2015) at state and LGA levels and the spatial locations of National Agricultural Research Systems.

Nigeria is a particularly important country for assessing complementarity between PI and PEA on returns to agricultural inputs/services. Historically, in Nigeria, a relatively low share of PE has been allocated to agriculture, given the dominance of the sector as the source of primary employment (Takeshima et al. 2020). Nigeria is also characterized by highly diverse agroecological production environments, such as soil types,[3] while also having an underdeveloped NARS system which cause significant variations in spillover potentials of improved varieties (Takeshima 2019).

The findings of our analyses suggest that, generally, marginal returns to agricultural inputs/services (fertilizer, agricultural mechanization, irrigation, extension, agricultural equipment, and family labor) are often raised by PI that raises overall AS (through R&D locations), as well as increased PEA-share by subnational governments. There is often complementarity between these PI and PEA, particularly for extension services, investment in agricultural equipment, irrigation, and in the northern part of the country.

The remainder of this paper has the following structures. Section 2 briefly describes the theoretical roles of PI and PEA. Section 3 discusses empirical methodology. Section 4 describes data, and section 5 presents descriptive statistics. Section 6 discusses the results. Lastly, section 7 concludes.

2 Roles of public investments and public expenditures for the productivity of agricultural inputs/services

PI tend to focus on medium-to-long-term outcomes, whereas PEA focus on more short-term and immediate outcomes, yet both are potential sources of productivity improvement in agriculture.

Agricultural R&D often constitutes a significant part of PI in agriculture (Evenson & Gollin 2003; Byerlee & Lynam 2020), particularly and in addition to agricultural R&D by both the International Agricultural Research Centers and NARS (Evenson & Gollin 2003; Walker & Alwang 2015; Lynam et al. 2016). Agricultural R&D can contribute to productivity improvement by directly improving the quality of technologies and inputs/services, as well as services like mechanization hiring services. Because of the spatial variations in spillover potentials, given the heterogeneity of agroclimatic conditions and location-specificity of agricultural technologies, locations of agricultural R&D have become potentially important drivers of medium-term productivity variations across space.

[3]Nigeria has the largest number of soil types in SSA based on FAO et al. (2012).

PEA (which focus more on the short-term) can potentially contribute to enhancing the productivity of agricultural inputs/services through various mechanisms. Typically, the type of spending classified under the agriculture, forestry, and fisheries expenditures include (IMF 2001; Fan & Saurkar 2012, p. 23–25):

- administration of agricultural affairs and services
- conservation, reclamation, or expansion of arable land; agrarian reform and land settlement
- supervision and regulation of the agricultural industry
- construction or operation of flood-control, irrigation, and drainage systems, or grants, loans, or subsidies for such work
- operation/support of programs/schemes to stabilize or improve farm prices and farm incomes
- operation or support of extension services or veterinary services to farmers, pest-control services, crop inspection services, crop grading services
- production and dissemination of general information, technical documentation, and statistics on agricultural affairs and services
- compensation, grants, loans, or subsidies to farmers in connection with agricultural activities, or payments for restricting or encouraging output of a particular crop, or for allowing land to remain uncultivated.

Public expenditures for these functions have the potential to directly or indirectly effect the productivity of various agricultural inputs/services by improving, for example, quality of inputs supplied (through regulation and certification, among others), conditions of farmland where inputs/services are applied, as well as quality of extension services accessed by farmers (quality of the information provided through extension officers).

Furthermore, as PI, including agricultural R&D, can potentially enhance total factor productivity (e.g., Evenson & Gollin 2003), PI could have complementary roles with PEA in enhancing the productivity of agricultural inputs/services.

3 Empirical methodology

Our goal is to examine how PEA and PI affect productivity and income returns to agricultural inputs/services at farm household levels. To do so, we assess the effects of the use of various agricultural inputs/services on agricultural production and incomes at farm household levels and assess how they differ qualitatively across locations differentiated by PEA and PI.

To this end, our primary empirical specification is what is often referred to as a stratified difference-in-difference propensity score matching (DID-PSM) method. First, by exploiting the panel nature of the data as described below, we combine the PSM method with DID. DID-PSM improves over a standard PSM, as the former can control for unobserved agents' specific effects, adding validity to the unconfoundedness assumption of PSM applied to DID transformed outcome variables (Heckman et al. 1997; Heckman et al. 1998; Smith & Todd 2005). DID-PSM has been increasingly used in impact evaluation studies (e.g., Todo 2011; Mason et al. 2017; Tranchant et al. 2019; Takeshima et al. 2021b).

We then stratify samples into groups based on PEA and PI, estimate DID-PSM for each group, and compare qualitative differences in estimated results across these groups to infer how the results vary depending on PEA and PI. Stratified PSM has been used in the past literature (e.g., Takeshima & Yamauchi 2012), and this study extends it to DID-PSM.

Specifically, our estimation proceeds as the following: the average treatment effects on the treated (ATT) for using agricultural inputs/services *k* is estimated as (modified from exposition in Villa 2016),

$$DID_{PSM} = \{E(Y_{i,t=1}|D_{i,t=1} = 1, C_i = 1) - \omega_i \times E(Y_{i,t=1}|D_{i,t=1} = 0, C_i = 0)\} - \{E(Y_{i,t=0}|D_{i,t=0} = 0, C_i = 1) - \omega_i \times E(Y_{i,t=0}|D_{i,t=0} = 0, C_i = 0)\} \quad (1)$$

where $Y_{i,t}$ is the set of outcomes of interest for farm household i at period $t = 0$ (base period) or $t = 1$ (follow-up period). $D_{i,t} = 1$ if farm households i switches from non-users of inputs/services at $t = 0$ to users of inputs/services at $t = 1$, and $D_{i,t} = 0$ is otherwise. By definition, $D_{i,t=0} = 0$ for all households. $C_i = 1$ if farm household i is the one that becomes $D_{i,t=1} = 1$ at $t = 1$ ($C_i = 0$ if otherwise).

The method (1) improves over standard DID by weight ω_i, which is defined in various ways by the propensity of i to use more agricultural inputs/services,

$$p_i = \Pr(C_i = 1|X_{i,t=0}) \quad (2)$$

which is a function of agent i's exogenous, observable characteristics X_i at the pre-intervention period.

The translation of p_i to w_i depends on the matching method used in PSM. In our primary specification, we use a nearest-neighbor method with a caliper, which has generally been suggested as more consistent than other matching methods (e.g., Caliendo & Kopeinig 2008). We then also estimate kernel matching methods to check the robustness of the results.

As is described in later section, our primary data cover three waves of panel data. The periods $t = 1$ and $t = 0$ are defined respectively for each wave; $t = 1$ refers to wave 2 (wave 3) if $t = 0$ refers to wave 1 (wave 2).

Generating stratified groups by PEA-share and PI

DID-PSM from (1) and (2) are estimated by stratifying samples into sub-groups based on the share of PEA to total PE by the local governments (hereafter PEA-share) and AS with agricultural R&D locations (an indicator of PI), as in Table 1. Specifically, samples are stratified first by the median level of changes in PEA-share between survey waves, and then by the median level of AS. Consequently, four sub-samples are generated: (a) high AS and a relative increase in PEA-share (between survey waves); (b) high AS and a relative decrease in PEA-share; (c) low AS and relative increase in PEA-share; and (d) low AS and relative decrease in PEA-share.

PEA-shares are, as is described in the subsequent data section, calculated at LGA-level, as the average of PE by the LGA that household resides (own-LGA), all contiguous LGAs (neighbor-LGAs), as well as the state. They are also calculated based on average the survey year as well as two previous years leading up to it. Similar approaches have been used in recent studies on PE in Nigeria (e.g., Takeshima et al. 2020).

AS is a time-invariant variable and measures the similarity between farm location and the research locations in terms of soil and climate conditions. AS is considered an important indicator of spillover potentials of agricultural technologies, which significantly affect the spatial variations in agricultural productivity (Alston 2002; Evenson & Gollin, 2003; Walker & Alwang

2015; Lynam et al. 2016; Takeshima 2019). The appendix describes the construction of AS indicators in more detail.

AS is multi-dimensional in nature, much as agroclimatic conditions are measured multidimensionally. As is described in the appendix, agroclimatic conditions are characterized by several Principle-Component (PC) scores, and a different indicator of AS is defined for each PC score. In our analyses, we repeat stratification of sub-groups (Table 1) for each AS indicator corresponding to different PC scores, re-estimate the models, and show that our findings are largely robust across different indicators of AS.

Standard panel for inputs/services with fewer adoption samples

For certain agricultural inputs/services (such as mechanization services and irrigation) with fewer adopting farmer samples, DID-PSM estimations (1) and (2) are infeasible due to insufficient sizes of matched samples. For these inputs/services, we therefore estimate standard panel fixed-effects models which are more feasible but rely on more restrictive assumptions that adoptions of agricultural inputs/services are exogenous to the outcomes conditional on unobserved household fixed effects alone. Specifically, we estimate

$$Y_{it} = \alpha + \beta_D D_{it} + \beta_G G_{it} + \beta_{DG}(D_{it} \cdot G_{it}) + \beta_X X_{it} + u_i + \varepsilon_{it} \tag{3}$$

in which Y_{it}, D_{it} and X_{it} are the same set of variables defined earlier. G_{it} is PEA-share for the local government where household i is located. α and β are estimated parameters, u_i is the unobserved household-specific fixed effects, and ε_{it} is an idiosyncratic error term. The parameter β_{DG} measures how PEA-share affects the marginal returns to agricultural inputs/services to outcome variables. While (3) is more restrictive and require more caution in interpretation than DID-PSM method described above, it still offers useful indicative evidence.

We estimate (3) separately for high AS areas and low AS areas, and assess whether there are qualitative differences in β_{DG} between the two samples. For example, more positive β_{DG} in high AS areas compared to low AS areas would indicate some complementary effects of PEA and PI.

Standard panel for adoption equations

We supplement the above analyses by estimating how PI and PEA affect the adoption of agricultural inputs/services through,

$$D_{it} = \alpha + \beta_G G_{it} + \beta_{\sigma G}(\sigma_{ik} \cdot G_{it}) + \beta_P P_{it} + \beta_X X_{it} + u_i + \varepsilon_{it} \tag{4}$$

in which D_{it}, G_{it} and X_{it} are the same set of variables defined earlier, while P_{it} is the set of variables related to the prices of inputs/services, and σ_{ik} is the AS variable defined based on k-th Principal Component (PC) of agroclimatic conditions (defined in Appendix).

Outcome and inputs/services variables

Outcome variables Y_{it} include annual agricultural revenue and profit for the farm households. Inputs/service variables of our interests include fertilizer, agricultural mechanization (use of animal traction and/or tractors), irrigation, extension services from either the public or the private sector, agricultural equipment owned, and family labor.

Explanatory variables X

Explanatory variables X consist of household demographics, wealth, community-level shocks, infrastructure access, and contemporary as well as historical climates. All variables except historical climates are time-variant and are included in the panel fixed-effects method (3) as well.

Household demographics include the number of household members by gender and age group (children aged 19 years or younger, working-age members aged between 20 and 60, and elderly aged 61 years or older), as well as age and gender of the household head.

Wealth and capital include human capital (years of education completed by the household head), household asset values, and exogenous farmland endowment (which include farmland owned or distributed by the chiefs of the community or village) as well as the number of plots owned and the amount of remittances received by the household.

Access to institutions and infrastructure includes the physical distance to the nearest market and administrative center, as well as the number of key community organizations and institutions[4] that are present within the local community.

Agroclimatic variables include current and historical rainfall, temperature and drought; historical average of wind and solar radiation; terrain ruggedness; distance to the nearest major river; and soil properties (alkalinity, organic contents, soil texture and drainage characteristics, salinity, and sodicity). As is described in the appendix, all time-invariant agroclimatic variables are used in computing the AS indicators (σ_{ik}), while time-variant agroclimatic variables (current rainfall, temperature, and drought) are included in X_{it}.

Lastly, we included year dummies to control for year-specific effects, interacted with six geopolitical zone dummy variables.

4 Data

This study uses household-level data, state and LGA-level PE data, and agroclimatic spatial data for Nigeria. The household-level data come from three panel rounds of the Living Standard Measurement Study–Integrated Survey on Agriculture (LSMS-ISA) collected by Nigeria's National Bureau of Statistics (NBS) and the World Bank in 2010/11, 2012/13, and 2015/16 (NBS & World Bank 2016). LSMS-ISA consists of a sample of 5,000 nationally representative households in 2010/11 (wave 1). Ten households were randomly selected in wave 1 from each of the 500 enumeration areas (EAs) which were again randomly selected from all EAs defined by the NBS and re-interviewed in waves 2 and 3.

Household data are supplemented by state and LGA-level PE data for all of Nigeria's 37 states and 774 LGAs. These PE data are extracted from annual statistical bulletins and reports from the Central Bank of Nigeria and annual surveys conducted jointly by the Federal Ministry of Finance, the Central Bank of Nigeria (CBN), the National Bureau of Statistics (NBS), and the

---

[4]Community organizations include Village Development Committee, Agricultural Coop/Farmer Based Org (FBO), Savings & Credit Cooperatives, Business Associations, Women's Groups, Youth Groups, Political Groups, Cultural Groups, Health Committees, School Committees, Parent-Teacher Associations, any other NGOs, community police/watch groups, and disability associations.

Major institutions in the community include schools (nursery, government primary schools, community-day primary schools, and government secondary schools), health institutions (health centers, public hospitals, private hospitals, private clinics, private doctors/specialists, midwives, dentists, and pharmacies), communication related institutions (cell phone distributors, post offices, bus/minibus stops, main access roads and internet cafés), and other places (banks, microfinance institutions, police stations, markets, mosques or churches, community centers and fire stations).

Nigerian Communications Commission (NCC), available for the period from 2007 to 2015 (Government of Nigeria, 2015 and previous years). The data provide information on expenditures by function (i.e., economic affairs, general public services, defense, public order and safety, environmental protection, etc.). The spending on agriculture denoted PEA, is defined as part of the spending on *economic affairs*.

Spatial agroclimatic data, from which AS indicators are constructed, include Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) data (Funk et al. 2015); average annual temperature data (National Oceanic and Atmospheric Administration (NOAA)/OAR/ESRL PSD 2021); drought data from the Standardized Precipitation Evapotranspiration Index (SPEI) from Vicente-Serrano et al. (2010); solar radiation (NASA 2017); and the data of wind speed at 10 m above ground (the Climatic Research Unit of the University of East Anglia (Climatic Research Unit, 2021). The climate data cover the period from 1980 through 2015 and were extracted for the geographical coordinates of EAs reported in LSMS-ISA. Soil data are extracted from FAO et al. (2012). Furthermore, terrain ruggedness is calculated using the elevation data from GTOPO30 data (U.S. Geological Survey, 1996) and formula by Riley et al. (1999), while the distance to the nearest major river is extracted from Lehner et al. (2006).

5 Descriptive/qualitative statistics

Table 2 summarizes the descriptive statistics of PEA-share, as well as their changes across survey waves, among the samples of LSMS-ISA agricultural households. Following Takeshima et al. (2020), figures shown in Table 2 are averages of PEA-shares from own-LGA, neighbor-LGAs and the state government where the agricultural households reside. In addition, figures are averages over the previous 3 years for each round of survey waves (for example, for wave 1 of LSMS-ISA, we take averages of PEAs from 2008, 2009, and 2010).

PEA-shares are about 3.9% and 3.4% of total PE at mean and median, respectively, ranging from 0.0% to 28.3%, with standard deviations of 2.8%. The changes in PEA-shares across survey waves are typically 0.7–0.8 percentage points at mean and median, ranging from the minimum of -10.1 to the maximum of 8.1, with standard deviations of 1.9 percentage points. Standard deviations indicate considerable variations across LGAs or states (and thus across households depending on where they reside), as well as over time, which provide sources of variations in PEA related variables with which we can assess their effects on agricultural outcomes at household levels.

Table 3 summarizes the descriptive statistics of the outcome and input variables of our interests, with all waves combined. The agricultural households in our primary sample of interest are typically smallholders, with approximate average production revenues of 1,542 staple food equivalent kgs and crop profits of 770. The relatively high standard deviation suggests, however, that revenue and profit values are quite heterogeneous. The production values were primarily derived from crop production, and the remaining production values originated from livestock and other agricultural by-products. Approximately 1/3, 1/4, and 1/10 of them used fertilizer, used agricultural mechanization (either animal traction and/or tractors), and received some form of agricultural extension services (either by the private or public sector). About 3% of them used irrigation. On average, they own agricultural capital with value that is equivalent to 84 kg of staple food and used approximately 500 person-days of family labor over the course of 12 months. Between each survey round, fractions of samples switched from non-users to users of relevant inputs/services or increased their uses. For example, about 10% of samples in each round switched from non-users to users of fertilizer (while 90% of samples either did not change use status or switched from users to nonusers).

Table 4 summarizes the descriptive statistics of all control variables among the agricultural households, with all three survey waves combined. Most households are headed by adult males aged around 50 years of age, with average working-age members having 4.9 years of education, and about 2–3 children aged under 14, 3 working-age members aged between 15–60 and elderly in some households. Households have an average of 0.57 hectares (ha) of farmland obtained through outright purchase or distributed by community leaders, typically split over 2 plots. These households are also generally asset poor (with an average asset value of 190 per capita). They are typically located about 70 km from the nearest market or district administrative center. Most households are, however, in communities with community groups or institutional infrastructures of various types that provide public services in health, education, or other social services. Agroclimatically, sample households typically experienced rainfall and temperature that were higher than the historical average, with average z-values of around 1.0. Standard deviations of each variable suggest considerable heterogeneity in household characteristics, as well as long-term agroclimatic conditions.

Agroclimatic similarity indicators

PC-analyses, as described in the appendix, suggest that 6 PCs can explain approximately 75 percent of overall variations in agroclimatic conditions (Table A1 and Table A2 in the appendix). Therefore, we use 6 AS indicators with respect to agricultural research locations in our analyses. Using 6 AS indicators is also a common practice in related studies (e.g., Takeshima & Liu 2020).

These 6 AS indicators are also generally uncorrelated with each other (Table A3 in Appendix). Thus, including these AS indicators in our analyses allows us to take into account the multidimensional nature of agroclimatic conditions in assessing the roles of AS in the productivity of agricultural inputs/services.

6 Results

Table 5 through Table 9 present the effects of certain agricultural inputs/services (fertilizer, extension, agricultural equipment, and family labor) on agricultural revenues and profits, estimated from stratified DID-PSM (1). The balancing properties are satisfactory for all DID-PSM regressions, suggesting that the estimated effects in Table 5 through Table 9 can be consistently attributed to the change in relevant agricultural inputs/services between survey waves.

Similarly, Table 10 presents the supplementary results for agricultural mechanization and irrigation, estimated through standard panel (3). As was explained earlier, estimation (3) is more restrictive than DID-PSM but more feasible when the sample of adopters is small (irrigation), or inputs/services of interest are more heterogeneous (agricultural mechanization which includes both animal traction and tractors).

Before interpreting the overall patterns, individual results can be interpreted as the following. For example, the first rows for fertilizer (Table 5) suggest that, switching from not using fertilizer to using fertilizer between survey waves statistically significantly reduced the agricultural profit by 677 (equivalent to kg of staple crops evaluated in local price) on average, in areas that are characterized as low AS (based on the first principal component (PC1) of agroclimatic conditions) and experienced a decreased PEA-share during these survey waves (column (d)). However, similar effects on agricultural profits were statistically insignificant in areas with low AS but increased PEA-share (c), or in areas with high AS regardless of PEA-share changes. These patterns hold for other definitions of ACs based on PC2-6 of agroclimatic conditions. Results in Table 6 through Table 9 are interpreted in similar ways.

In Table 10, for example, in Northern Nigeria, in areas that are characterized as high AS (based on the first principal component (PC1) of agroclimatic conditions), one percentage–point increase in PEA-share would increase the marginal effects of mechanization adoption on agricultural profit by 82.342 (equivalent to kg of staple crops evaluated in local price). The estimates change to 70.799 if high AS is defined by PC2, and so forth.

Overall patterns

Results from Table 5 through Table 10 jointly suggest key patterns. Most importantly, results generally suggest that (i) higher AS and higher PEA-share raise the returns to agricultural inputs/services, and while these results do not always hold, the opposing evidence (that higher AS and higher PEA-share lower the returns to agricultural inputs/services) is much weaker; (ii) there is generally complementarity between AS and PEA in raising the returns to agricultural inputs/services; and (iii) these patterns are generally clearer in agricultural profits, than for agricultural revenues, suggesting that higher PEAs and AS help reduce production costs more than increasing outputs.

Regarding (i), positive effects of increased PEA-share on agricultural inputs/services are suggested if (a) is relatively more positive than (b), and if (c) is relatively more positive than (d). Similarly, positive effects of higher AS are suggested if (a) is relatively more positive than (c), and if (b) is relatively more positive than (d). These patterns hold for most results in Table 5 through Table 9. For example, for fertilizer (Table 5), (d) is generally significantly negative, while (c) is statistically insignificant (across various PCs that define AS). These indicate that in areas with low AS, decreasing the PEA-share makes the marginal return of fertilizer to agricultural profit significantly negative (so that using fertilizer is less profitable than not using it), while increasing the PEA-share makes marginal returns of fertilizer to agricultural profit insignificantly different from zero (so that using fertilizer is equally as profitable as not using it). While these differences are not clearly observed between (a) and (b), (a) is not significantly negative relative to (b), suggesting that in areas with high AS, while increasing the PEA-share may not raise marginal returns to fertilizer, it does not necessarily lower such return either. When limiting the sample to northern Nigeria, (a) becomes significantly more positive than (b) as well, suggesting that, even in areas with high AS, increasing PEA-share raises the marginal returns to fertilizer. Similarly, comparisons between (a) and (c), and (b) and (d) suggest that raising AS sometimes raises, but never lowers, returns to fertilizer. For extension (Table 7), (a) is sometimes more significantly positive than (b), while (b) is never significantly positive than (a). Similarly, (d) is never significantly positive than (c), suggesting that evidence lean toward positive effects of increased PEA-share on the marginal returns to accessing extension service. Similarly, comparisons between (a) and (c), and (b) and (d) suggest that, raising AS sometimes raises, but never lowers, returns to extension. Patterns are similar for family labor (Table 8). Results for agricultural equipment (Table 9) are somewhat ambiguous between (c) and (d) or (b) and (d), but (a) is generally more significantly positive than (b) or (c), suggesting on balance that higher AS and PEA-share raise returns to agricultural equipment. Similarly, significant coefficients in Table 10 are all positive, suggesting that increasing PEA-shares generally raise returns to mechanization and irrigation.

Regarding (ii), in Table 5 through Table 9 relative qualitative difference between (a) and (b), compared to the qualitative difference between (c) and (d). If the positive difference between (a) and (b) is more pronounced than the difference between (c) and (d), it can indicate that AS and PEA are complementary in raising the returns to agricultural inputs/services. For example, results for extension and agricultural equipment (Table 7 and Table 9) suggest that (a) is generally more significantly positive than (c), compared to the differences between (b) and (d), indicating complementarity between higher AS and higher PEAs in raising returns to extension and agricultural equipment on agricultural profit. Similarly, in Table 10, higher PEA-shares raise returns to irrigation more significantly in high AS areas than in low AS areas, suggesting their complementarity in raising returns to irrigation. Patterns are somewhat less clear for agricultural mechanization and family labor—there is no clear evidence that AS and PEA-share are clear substitutes. Some exceptions are fertilizer (Table 5) and agricultural mechanization (Table 10), in which positive effects of PEA-share are clearer in low AS areas than in high AS areas. However, when limiting the sample to Northern Nigeria, differences between high AS and low AS disappear for fertilizer (Table 6) and agricultural mechanization (Table 10). For fertilizer and mechanization, these results are particularly important because these inputs/services and technologies tend to be used more commonly by smallholders in northern Nigeria than in southern Nigeria (Takeshima & Nkonya 2014; Takeshima et al. 2013).

Robustness of results

Results from Table 5 through Table 10 are, as was described earlier, based on the measurement of particular PEA-shares (averaged over the 3 years leading up to the survey year, averaged over own LGA, all neighbor-LGAs, and state). While not shown, overall patterns implied by Table 5 through Table 10 are generally robust under different ways of calculating relevant PEA-shares, such as using shorter lag periods of PEA, as well as using only own-LGA. This is consistent with earlier studies (e.g., Takeshima et al. 2020) that results are generally robust against these variations.

Similarly, as was described earlier, results on DID-PSM from Table 5 through Table 9 use specific matching methods. While not shown, overall patterns are generally consistent when using alternative matching methods (e.g., kernel matching).

Adoption of inputs/services

Table 11 presents the effects of PEAs and AS on the adoptions, estimated through (4). There is some evidence indicative of complementarity in higher AS and PEA-share, i.e., effects of increased PEA-shares on adoptions are further raised by higher AS, especially extension/services, irrigation, and agricultural mechanization. These patterns are consistent with the hypotheses that higher returns enabled by increased PEA-share and AS also encourage adoptions of these inputs/services.

However, unlike returns to agricultural inputs/services from Table 5 through Table 10, results are less robust for the adoptions of these inputs/services in Table 11. For example, effects of PEA-shares do not significantly vary across AS regardless of PCs used for defining AS; coefficients are never statistically significant for fertilizer, agricultural equipment, and are only occasionally significant for agricultural mechanization, extension, and irrigation.

The exact causes of apparent gaps between effects on returns to inputs/services and adoptions/investments in these inputs/services, in regard to the complementarity between PEA and AS need to be more thoroughly investigated in future studies. Nonetheless, these results suggest that there is scope for enhancing the overall agricultural productivity through efforts that facilitate the adoptions/investments in agricultural inputs/services by paying greater attention to the spatial variations in spillover potentials and PEA-shares. For example, in the short-term, adoption promotion efforts can focus more on areas with higher AS and where PEA-shares have relatively increased recently. Similarly, efforts to raise PEA-shares may focus more on areas with higher AS. At the same time, in the medium-to-long terms, it is important to increase PI in ways that raise overall AS (including, for example, through expanding the locations of agricultural R&D). This is particularly critical for fundamentally improving inclusiveness by creating conditions that raise returns to agricultural inputs/services in areas that are currently characterized with low AS.

7 Conclusions

The roles of public investments (PI) and public expenditures for agriculture (PEA) on agrifood sector development have long been recognized in developing countries like Nigeria. However, knowledge gaps remain as to how exactly they can enhance productivity and efficiency in the agrifood sector and how longer-term PI such as agricultural R&D, and short-term interventions through PEA complement each other. Obtaining such insights are particularly important in countries like Nigeria, where PI and PEA-share are, arguably, low given the sector's persistent importance as the main source of employment and food security among the poor.

This study attempted to partly fill this gap by assessing how spatial variations in profitability impacts of agricultural inputs/services have been affected by the shares of local governments' PEA and AS that affect spillover potentials of technologies developed by National Agricultural R&D, a key component of PI in agriculture in Nigeria. In general, the findings suggest that higher AS and higher PEA-share raise the marginal returns to agricultural inputs/services and that there is complementarity between AS and PEA in raising productivity. These patterns are particularly clear for returns to extension services, investment in agricultural equipment, irrigation, and in northern Nigeria. The results also suggest that, in the short-term, promoting increased adoptions of these inputs/services, particularly in areas with high AS and increased PEA, can enhance overall productivity. At the same time, in the medium-to-long term, increasing PI in ways that raise overall AS (including, for example, through expanding the locations of agricultural R&D) can further increase agricultural productivity in more inclusive ways.

References

Alston JM. (2002). Spillovers. *Australian Journal of Agricultural and Resource Economics 46*(3): 315–46.

Burke WJ, E Frossard, S Kabwe & TS Jayne. (2019). Understanding fertilizer adoption and effectiveness on maize in Zambia. *Food Policy 86*, 101721.

Byerlee D & JK Lynam. (2020). The development of the international center model for agricultural research: A prehistory of the CGIAR. *World Development, 135*, 105080.

Climatic Research Unit (CRU). (2021). *10m windspeed.* University of East Anglia.

Coelli T, S Rahman & C Thirtle. (2003). A stochastic frontier approach to total factor productivity measurement in Bangladesh crop agriculture, 1961–92. *Journal of International Development 15*, 321–333.

Comas J, D Connor, MEM Isselmou L Mateos & H Gómez-Macpherson. (2012). Why has small-scale irrigation not responded to expectations with traditional subsistence farmers along the Senegal River in Mauritania?. *Agricultural Systems, 110*, 152-161.

Dadi L, M Burton & A Ozanne. (2004). Duration analysis of technological adoption in Ethiopian agriculture. *Journal of Agricultural Economics, 55*(3), 613–631.

Davis K, SC Babu & C Ragasa. (2020). *Agricultural Extension: Global Status and Performance in Selected Countries.* Washington, DC: International Food Policy Research Institute. https://doi .org/10.2499/9780896293755.

Donkor E, S Onakuse, J Bogue & I De Los Rios-Carmenado. (2019). Fertiliser adoption and sustainable rural livelihood improvement in Nigeria. *Land Use Policy, 88*, 104193.

Evenson R & LE Westphal. (1995). *Technological Change and Technology Strategy.* In J Behrman & TN Srinivasan (Eds.), *Handbook of Development Economics*. 2209-2299. Amsterdam: Elsevier.

Evenson R & D Gollin. (2003). *Crop Variety Improvement and Its Effect on Productivity: The Impact of International Agricultural Research*. Wallingford, UK: CABI.

Fan S & A Saurkar. (2012). *Public Spending for Agriculture in Africa: Definition, measures and trends*. In Mogues T & S Benin. (eds). *Public expenditures for agricultural and rural development in Africa*. Routledge.

Feder G & DL Umali. (1993). The adoption of agricultural innovations: A review. *Technological Forecasting and Social Change 43*(3-4, Special Issue), 215-239.

FAO (Food and Agriculture Organization) /IIASA (International Institute for Applied Systems Analysis) /ISRIC (International Soil Reference and Information Centre) /ISSCAS (Institute of Soil Science – Chinese Academy of Sciences) /JRC (Joint Research Centre of the European Commission). 2012. *Harmonized World Soil Database (version 1.2).* Rome: FAO; Laxenburg, Austria: IIASA. http://webarchive.iiasa.ac.at/Research/LUC/External-World-soil-database/HTML/.

Funk C, P Peterson, M Landsfeld, D Pedreros, J Verdin, S Shukla, G Husak, J Rowland, L Harrison, A Hoell & J Michaelsen. 2015. The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific Data 2*(1), 1–21.

Fuwa N, C Edmonds, P Banik. (2007). Are small-scale rice farmers in eastern India really inefficient? Examining the effects of microtopography on technical efficiency estimates. *Agricultural Economics 36*(3), 335-346.

Government of Nigeria. (2015). *Federal Ministry of Finance, Office of the Accountant General of the Federation, CBN/NBS/NCC 2015 Collaborative Survey and Staff Estimates*; Various years. Computer Disk.

Heckman J, H Ichimura & P Todd. (1997). Matching as an econometric evaluation estimator: evidence from evaluating a job training programme. *Review of Economic Studies 64*(4), 605–654.
Heckman J, H Ichimura, J Smith & P Todd. (1998). Characterizing selection bias using experimental data. *Econometrica 66*(5), 1017–1098.
International Monetary Fund (IMF). (2001). *Government Finance Statistics Manual*. Washington DC.
Lagakos D & ME Waugh. (2013). Selection, Agriculture, and Cross-Country Productivity Differences. *Amer Econ Rev 103*(2): 948-80.
Lehner B, K Verdin & A Jarvis. (2006): *HydroSHEDS Technical Documentation*. World Wildlife Fund US, Washington, DC. Available at http://hydrosheds.cr.usgs.gov.
Lynam J, N Beintema, J Roseboom & O Badiane. (2016). *Agricultural Research in Africa: Investing in Future Harvests*. Washington DC: IFPRI.
Mason NM, A Wineman, L Kirimi & D Mather. (2017). The effects of Kenya's 'smarter' input subsidy programme on smallholder behaviour and incomes: do different quasi-experimental approaches lead to the same conclusions? *Journal of Agricultural Economics 68*(1), 45–69.
Michler JD, E Tjernström, S Verkaart & K Mausch. (2019). Money matters: The role of yields and profits in agricultural technology adoption. *American Journal of Agricultural Economics*, 101(3), 710–731.
Mogues T & S Benin. (2012). Public expenditures for agricultural and rural development in Africa. *Routledge.*
National Bureau of Statistics of Nigeria (NBS) and World Bank. (2016). *Living Standard Measurement Study – Integrated Survey on Agriculture Wave 1 – 3*. Available at http://surveys.worldbank.org/lsms/programs/integrated-surveys-agriculture-ISA/nigeria. Accessed on October 1, 2019.
National Aeronautics and Space Administration, 2017. NASA surface meteorology and solar energy: Global data sets. https://power.larc.nasa.gov/. Accessed April 15, 2017.
Njuki E & BE Bravo-Ureta. (2019). Examining irrigation productivity in US agriculture using a single-factor approach. *Journal of Productivity Analysis, 51*(2-3), 125–136.
National Oceanic and Atmospheric Administration (NOAA). 2021. *CPC global temperature data*. Available at https://psl.noaa.gov/. Accessed on October 1, 2021.
O'Gorman M & M Pandey. (2010). Cross-country disparity in agricultural productivity: Quantifying the role of modern seed adoption. *Journal of Development Studies, 46*(10), 1767–1785.
Otsuka K & D Larson. (2012). *An African Green Revolution: Finding Ways to Boost Productivity on Small Farms*. Springer Science & Business Media.
Riley S, S DeGloria & R Elliot. (1999). a terrain ruggedness index that quantifies topographic heterogeneity. *Intermoun. J. Sci. 5*(1–4), 23–27.
Rurinda J, S Zingore, JM Jibrin, T Balemi, K Masuki, JA Andersson, MF Pampolino, I Mohammed, J Mutegi, AY Kamara, B Vanlauwe & PQ Craufurd. (2020). Science-based decision support for formulating crop fertilizer recommendations in sub-Saharan Africa. *Agricultural systems, 180*, 102790.
Smith J & P Todd. (2005). Does matching overcome LaLonde's critique of nonexperimental estimators? *Journal of Econometrics 125*(1–2), 303–353.
Takeshima H & F Yamauchi. (2012). Risks and farmers' investment in productive assets in Nigeria. *Agric. Econ. 43*(2), 143–153.

Takeshima H, A Nin Pratt & X Diao. (2013). Mechanization and agricultural technology evolution, agricultural intensification in sub-Saharan Africa: typology of agricultural mechanization in Nigeria. *American Journal of Agricultural Economics 95*(5), 1230–1236.

Takeshima H & E Nkonya. (2014). Government fertilizer subsidy and commercial sector fertilizer demand: Evidence from the Federal Market Stabilization Program (FMSP) in Nigeria. *Food Policy 47*, 1–12.

Takeshima H, E Edeh, A Lawal & M Ishiaka. (2015). Characteristics of private-sector tractor service provisions: Insights from Nigeria. *Developing Economies 53*(3), 188–217.

Takeshima H, R Adhikari, S Shivakoti, BD Kaphle & A Kumar. (2017). Heterogeneous Returns to Chemical Fertilizer at the Intensive Margins: Insights from Nepal. *Food Policy 69*, 97-109.

Takeshima H. (2019). Geography of plant breeding systems, agroclimatic similarity, and agricultural productivity: an insight from Northern Nigeria. *Agricultural Economics 50*(1), 67-78.

Takeshima H & Y Liu. (2020). Smallholder mechanization induced by yield-enhancing biological technologies: Evidence from Nepal and Ghana. *Agricultural Systems 184*, 102914.

Takeshima H, J Smart, HO Edeh, MA Oyeyemi, B Balana & KS Andam. (2020). *Public Expenditures on Agriculture at Subnational-Levels and Household-Level Agricultural Outcomes in Nigeria*. IFPRI DP 01952.

Takeshima H, J Smart & X Diao. (2021). *Public expenditure's role in reducing poverty and improving food and nutrition security: Preliminary cross-country insights based on SPEED data.* IFPRI DP 02051.

Takeshima H, F Yamauchi, D Bawa, SO Kamaldeen, H Edeh & MA Hernandez. (2021b). *Solar-powered cold-storages and sustainable food system transformation: Evidence from horticulture markets interventions in northeast Nigeria.* IFPRI DP 02047.

Todo Y. (2011). Impacts of aid-funded technical assistance programs: Firm-level evidence from the Indonesian foundry industry. *World Development 39*(3), 351-362.

Tranchant JP, A Gelli, L Bliznashka, AS Diallo, M Sacko, A Assima, EH Siegel, E Aurino & E Masset. (2019). The impact of food assistance on food insecure populations during conflict: Evidence from a quasi-experiment in Mali. *World Development 119*, 185–202.

USGS (U.S. Geological Survey), 1996. *GTOPO30.* USGS Center for Earth Resources Observation and Science, Sioux Falls, US.

Vicente-Serrano SM, S Beguería & JI López-Moreno. 2010. A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. *Journal of Climate 23*(7), 1696–1718.

Villa JM. (2016). diff: Simplifying the estimation of difference-in-differences treatment effects. *The Stata Journal, 16*(1), 52–71.

Walker TS & J Alwang. (2015). *Crop improvement, adoption and impact of improved varieties in food crops in Sub-Saharan Africa*. CABI.

Xie H, L You & H Takeshima. (2017). Invest in small-scale irrigated agriculture: A national assessment on potential to expand small-scale irrigation in Nigeria. *Agricultural Water Management 193*, 251–264.

Table 1. Stratification of sub-groups of farm households

Category	PEA share relatively increased between survey waves (time-variant)	PEA share relatively decreased between survey waves (time-variant)
Agroclimatic similarity – high (time-invariant)	(a)	(b)
Agroclimatic similarity – low (time-invariant)	(c)	(d)

Source: Authors.

Table 2. Shares of public expenditure for agricultural sector and their changes over survey waves (%, values among agricultural households)

Variables	Sample size (three waves combined)	**mean**	**median**	**minimum**	**maximum**	**Standard deviations**
PEA - shares (%)	10,093	3.872	3.354	0.000	28.295	2.828
Changes in PEA across waves	6,631	-0.777	-0.670	-10.097	8.092	1.859

Source: Authors' calculations based on Government of Nigeria (2015) and LSMS-ISA data.
Note: LGA – Local Government Area. PEA = Public expenditures for agriculture.

Table 3. Descriptive statistics of outcome variables and inputs/services variables

Variables	Unit	Mean	Standard deviation
Outcome variables			
Crop production revenue	value / household	1541.858	3299.283
Crop profit	value / household	770.187	1510.555
Input variables			
Fertilizer use	1 = used	0.362	0.481
Agricultural extension (private and public combined)	1 = used	0.090	0.286
Agricultural mechanization (animal traction and/or tractors)	1 = used	0.238	0.426
Irrigation	1 = used	0.031	0.173
Agricultural capital value	value / household	83.775	332.387
Family labor	person-days / year / household	507.884	520.539
Input variables – increased between waves			
Fertilizer use	1 = switched to user (0 = if no change or switched to nonuser)	0.099	0.299
Agricultural extension (private and public combined)	1 = switched to user (0 = if no change or switched to nonuser)	0.051	0.220
Agricultural mechanization (animal traction and/or tractors)	1 = switched to user (0 = if no change or switched to nonuser)	0.066	0.248
Irrigation	1 = switched to user (0 = if no change or switched to nonuser)	0.014	0.119
Agricultural capital value	1 = increased (0 = if no change or decreased)	0.438	0.496
Family labor	1 = increased (0 = if no change or decreased)	0.412	0.492

Source: Authors based on LSMS-ISA.
"value" refers to real value measured in equivalent of kilogram of local staple food evaluated at local staple food price.

Table 4. Descriptive statistics (agricultural household samples – combined over all 3 waves)

Variables	mean	std.err
Household head age (years)	51.935	15.147
Household head gender (female = 1)	0.143	0.350
Education of working-age members (years, average)	4.850	4.136
Household size (0 – 14, female)	1.243	1.339
Household size (0 – 14, male)	1.382	1.443
Household size (15 – 60, female)	1.547	1.093
Household size (15 – 60, male)	1.332	1.135
Household size (61 or above, female)	0.159	0.388
Household size (61 or above, male)	0.225	0.420
Livestock (value, 1000)	2.155	12.031
Asset per capita (value, natural log)	191.482	1157.76
Farmland outright purchased or community-distributed (ha)	0.570	2.603
Remittances received per capita (value, natural log)	0.048	2.030
Number of farm plots owned (number)	1.763	1.225
Distance to the nearest market (km)	70.837	39.915
Distance to the nearest administrative center (km)	73.017	55.067
Number of community organizations	5.605	3.247
Number of major institutions in the community	6.971	4.808
Community experienced events during survey year (yes = 1)		
Drought	0.051	0.220
Flood	0.173	0.378
Crop disease / pests	0.080	0.271
Livestock disease	0.045	0.207
Human epidemic disease	0.031	0.174
Sharp change in prices	0.161	0.368
Massive job lay-offs	0.017	0.131
Loss of key social services	0.024	0.152
Power outage(s)	0.041	0.198
Other bad events	0.102	0.302
Development project	0.095	0.293
New employment opportunity	0.024	0.153
New health facility	0.061	0.239
New road	0.083	0.276
New school	0.071	0.257
Improved transportation services	0.060	0.237
On-grid electricity	0.028	0.166
Off-grid electricity	0.007	0.084
Other good events	0.101	0.301
Rainfall in current year (z-value based on historical distribution)	1.002	1.513
Average daily temperature in current year (z-value based on historical distribution)	1.021	0.942
Annual rainfall (mm) (average 1980-2009)	1199.244	562.089
Average daily temperature (average 1980-2009)	26.941	1.077
Drought index (average 1980-2009)	-0.143	0.081
Average wind speed at 10 meter above ground (meter per second)	2.496	0.563
Solar radiation (kwh/m^2) (average 1980-2009)	5.288	0.546
Soil alkalinity (pH)	5.988	0.716
Soil organic content (g / kg of soil)	0.888	0.282
Soil texture (% medium)	0.596	0.298
Soil texture (% coarse)	0.348	0.315
Soil texture (% fine)	0.054	0.136
Soil salinity (deciSiemens per metre)	0.260	1.073
Soil sodicity (% of soil)	3.119	2.310
Soil with poor drainage (%)	0.235	0.313
Soil with excess drainage (%)	0.120	0.244
Terrain ruggedness index	25.488	38.295
Distance to the nearest major river (Geographical minutes)	0.017	0.012

Source: Authors' calculations based on LSMS-ISA data.

Note: "Value" is a real term, measured in kg of staple food evaluated by their local prices.

Table 5. Effects of fertilizer use on agricultural profit and agricultural revenue (estimated through (1) and (2))

Category	PC defining AS	High AS	High AS	Low AS	Low AS
		Increased PEA-share	Decrease PEA-share	Increased PEA-share	Decrease PEA-share
		(a)	(b)	(c)	(d)
Agricultural profit (value)	PC – 1	-116.978	-3.196	-29.321	-676.892***
	PC – 2	49.438	-371.209	-41.241	-464.977*
	PC – 3	-62.133	-298.391	-158.390	-684.284***
	PC – 4	-48.233	352.585	-62.591	-624.843***
	PC – 5	-81.051	-260.871	61.077	-607.660**
	PC – 6	-146.175	-324.665	-82.130	-793.614***
Agricultural revenue (proportional change)	PC – 1	0.359**	-0.429	0.435***	0.112
	PC – 2	0.215*	-0.255	0.434***	0.111
	PC – 3	0.177*	0.202	0.409**	-0.258
	PC – 4	-0.026	0.152	0.593***	-0.236
	PC – 5	0.075	-0.133	0.568***	0.249
	PC – 6	0.368***	0.040	0.179	-0.102
Sample size: control – treatment – treatment (on support)[a]	PC – 1	1329-176-168	612-69-54	1408-241-229	1077-171-162
	PC – 2	1202-186-177	874-98-93	1519-229-215	747-141-130
	PC – 3	1393-235-223	881-103-95	1361-180-171	767-136-128
	PC – 4	1351-214-203	687-87-71	1381-201-191	947-152-144
	PC – 5	1575-202-192	772-135-119	1189-215-203	894-108-103
	PC – 6	1368-208-198	904-117-112	1373-207-194	763-122-115

Source: Authors' estimations. Asterisks indicate statistical significance: *** 1% ** 5% *10%

Note: PEA = Public expenditures for agriculture; AS = agroclimatic similarity.

[a]In Table 5 through Table 9, "treatment" refers to the so-called adopters of inputs/services (those with $D_{i,t=1} = 1$ and $D_{i,t=0} = 0$, in other words, those who switched to user of respective agricultural inputs/services, or increased agricultural equipment values, or family labor use, between waves), and "control" refers to all the rest. Samples of "treatment (on-support)" are treatment group samples for whom matched samples can be found among control samples, and thus included in the analyses.

Table 6. Effects of fertilizer use on agricultural profit and agricultural revenue (estimated through (1) and (2)) (Northern Nigeria)

Category	PC defining AS	High AS Increased PEA-share (a)	High AS Decrease PEA-share (b)	Low AS Increased PEA-share (c)	Low AS Decrease PEA-share (d)
Agricultural profit (value)	PC – 1	127.533	-766.248**	-292.071	-500.634**
	PC – 2	112.738	-660.345*	101.096	-777.003***
	PC – 3	310.466	-856.781**	-287.402	-754.819***
	PC – 4	-184.836	-680.774**	-76.702	-766.115***
	PC – 5	-16.237	-947.241***	205.408	-349.032
	PC – 6	-169.396	-377.060*	62.166	-466.605
Agricultural revenue (proportional change)	PC – 1	0.319*	-0.151	0.537**	0.026
	PC – 2	0.315	-0.435*	0.635***	0.043
	PC – 3	0.148	0.067	0.455*	-0.097
	PC – 4	0.004	0.044	0.920***	-0.081
	PC – 5	0.181	-0.514**	0.857***	0.207
	PC – 6	0.593***	-0.158	0.019	0.002
Sample size: control – treatment – treatment (on support)[a]	PC – 1	830-135-129	426-75-65	645-91-79	715-136-123
	PC – 2	691-105-91	500-82-77	821-121-115	624-129-120
	PC – 3	729-119-108	517-84-80	723-108-99	591-127-117
	PC – 4	782-111-98	480-94-83	723-116-108	662-117-112
	PC – 5	824-118-110	448-106-94	648-108-92	681-105-98
	PC – 6	678-117-107	589-103-98	821-109-101	549-108-97

Source: Authors' estimations. Asterisks indicate statistical significance: *** 1% ** 5% *10%

Note: PEA = Public expenditures for agriculture; AS = agroclimatic similarity.

Table 7. Effects of using extension services on agricultural profit and agricultural revenue (estimated through (1) and (2))

Category	PC defining AS	High AS Increased PEA-share **(a)**	High AS Decrease PEA-share **(b)**	Low AS Increased PEA-share **(c)**	Low AS Decrease PEA-share **(d)**
Agricultural profit (value)	PC – 1	492.074*	1145.893**	190.685	-158.723
	PC – 2	247.096	348.400	-59.100	-93.689
	PC – 3	-170.847	-174.551	271.091	195.388
	PC – 4	471.960*	27.752	238.023	35.659
	PC – 5	309.283	269.650	119.820	-346.571
	PC – 6	593.092**	-201.364	-171.388	316.852
Agricultural revenue (proportional change)	PC – 1	0.169	0.478	0.414**	0.584***
	PC – 2	0.338*	0.242	0.202	0.451
	PC – 3	0.065	0.218	0.437*	0.490
	PC – 4	0.334*	0.250	0.308	0.459
	PC – 5	0.416***	0.572**	0.182	0.388
	PC – 6	0.610***	-0.070	0.073	0.633**
Sample size: control – treatment – treatment (on support)[a]	PC – 1	1339-75-72	584-34-30	1451-99-95	1025-120-102
	PC – 2	1197-83-75	875-79-66	1545-86-82	679-75-65
	PC – 3	1491-93-89	802-83-75	1329-76-72	747-71-62
	PC – 4	1454-90-86	562-70-49	1284-79-72	927-84-74
	PC – 5	1547-85-81	737-80-57	1271-84-76	872-74-65
	PC – 6	1361-88-83	811-65-43	1345-81-77	787-89-83

Source: Authors' estimations. Asterisks indicate statistical significance: *** 1% ** 5% *10%

Note: PEA = Public expenditures for agriculture; AS = agroclimatic similarity.

Table 8. Effects of greater family labor use on agricultural profit and agricultural revenue (estimated through (1) and (2))

Category	PC defining AS	High AS Increased PEA-share	High AS Decrease PEA-share	Low AS Increased PEA-share	Low AS Decrease PEA-share
		(a)	**(b)**	**(c)**	**(d)**
Agricultural profit (value)	PC – 1	209.827*	140.068	112.745	131.670
	PC – 2	103.437	152.993	296.956***	137.930
	PC – 3	261.561**	126.330	188.434*	209.400
	PC – 4	313.229***	264.902*	167.443	143.351
	PC – 5	187.927*	263.723*	242.808**	136.549
	PC – 6	233.766**	110.653	-6.439	136.671
Agricultural revenue (proportional change)	PC – 1	0.278***	0.190*	0.035	0.189**
	PC – 2	0.305***	0.441***	0.103	0.097
	PC – 3	0.114	0.228***	0.303***	0.221**
	PC – 4	0.314***	0.147	0.125	0.250**
	PC – 5	0.144*	0.242**	0.063	0.196*
	PC – 6	0.156*	0.228**	0.124	0.205**
Sample size: control – treatment – treatment (on support)[a]	PC – 1	928-649-617	562-462-437	986-762-724	825-793-754
	PC – 2	798-675-642	737-644-612	1113-730-694	645-603-573
	PC – 3	1000-710-675	718-653-621	911-695-661	675-603-573
	PC – 4	1000-678-645	627-499-475	911-727-691	753-748-711
	PC – 5	1045-810-770	693-576-548	870-598-569	689-676-643
	PC – 6	938-707-672	727-670-637	973-698-664	655-577-549

Source: Authors' estimations. Asterisks indicate statistical significance: *** 1% ** 5% *10%

Note: PEA = Public expenditures for agriculture; AS = agroclimatic similarity.

Table 9. Effects of increased agricultural equipment value on agricultural profit and agricultural revenue (estimated through (1) and (2))

Category	PC defining AS	High AS Increased PEA-share	High AS Decrease PEA-share	Low AS Increased PEA-share	Low AS Decrease PEA-share
		(a)	**(b)**	**(c)**	**(d)**
Agricultural profit (value)	PC – 1	212.074*	-242.090	-212.930**	-65.028
	PC – 2	175.186	-337.487**	-128.276	-114.289
	PC – 3	138.030	15.865	114.161	-263.835**
	PC – 4	86.201	-321.834**	98.189	-100.834
	PC – 5	99.234	-237.714	21.732	-132.875
	PC – 6	28.732	-82.379	139.206	-243.066*
Agricultural revenue (proportional change)	PC – 1	0.463***	0.172	0.017	0.151
	PC – 2	0.327***	0.063	0.013	0.260**
	PC – 3	0.268***	0.135	0.157	0.223**
	PC – 4	0.171*	0.199*	0.132	0.194**
	PC – 5	0.223**	0.141	0.102	0.093
	PC – 6	0.180*	0.192*	0.274**	0.140
Sample size: control – treatment – treatment (on support)[a]	PC – 1	961-616-584	640-384-362	1072-676-643	910-708-673
	PC – 2	861-612-582	821-560-532	1169-674-641	713-529-503
	PC – 3	1038-672-639	804-567-539	992-614-584	748-530-504
	PC – 4	1019-659-627	662-464-441	1011-627-595	878-623-592
	PC – 5	1088-767-729	782-487-463	948-520-494	762-603-573
	PC – 6	988-657-625	820-572-544	1042-629-598	715-517-492

Source: Authors' estimations. Asterisks indicate statistical significance: *** 1% ** 5% *10%

Note: PEA = Public expenditures for agriculture; AS = agroclimatic similarity.

Table 10. Effects of increased PEA-share on the marginal returns to mechanization and irrigation (estimated through (3)) (Effects of one percentage point increase in PEA-share)

Category	PC defining AS	Agricultural mechanization (animal traction / tractors)				Irrigation	
		All geopolitical zones		Northeast and Northwest Geopolitical Zones Northeast and Northwest Geopolitical Zones			
		High AS	Low AS	High AS	Low AS	High AS	Low AS
Agricultural profit (value / household)	PC – 1	-33.974	52.073***	82.342**	46.539**	324.933***	-31.067
	PC – 2	3.551	66.700***	70.799**	53.878**	58.112	9.297
	PC – 3	46.920*	35.959*	72.241**	58.526***	52.592	24.800
	PC – 4	11.795	69.776***	62.098***	91.968***	125.732*	19.314
	PC – 5	7.129	58.521***	94.731***	53.412**	99.291**	31.296
	PC – 6	34.756*	41.492	59.566***	83.145**	49.227	55.287
Sample size		4894	4910	2000	2014	4992	4974
Agricultural revenue (proportional change)	PC – 1	-0.015	-0.002	0.018	-0.014	0.144***	0.000
	PC – 2	-0.014	-0.002	-0.013	-0.014	0.024	0.071
	PC – 3	-0.031	0.020	-0.031	0.003	0.039	0.072*
	PC – 4	-0.019	0.013	-0.032	0.026	0.023	0.033
	PC – 5	0.021	-0.013	0.015	-0.039*	0.081**	0.021
	PC – 6	-0.003	0.012	-0.013	-0.010	0.008	0.058*
Sample size		4977	4952	2000	2014	5046	5045

Source: Authors' estimations. Asterisks indicate statistical significance *10% **5% ***1%.

Note: Standard errors account for cluster-effects due to potential serial correlations within enumeration areas (EAs).
PC = principal component (of agroclimatic conditions)
AS = Agroclimatic similarity
PEA = Public expenditures for agriculture

Table 11. Combined effects of increased PEA-share and AS on input/service uses (estimated through (4)) (combined effects of 1 percentage point change in PEA-share and one-standard deviation change in AS indicator, on the one-standard deviation change in adoption indicator)

PC defining AS	Fertilizer	Agricultural mechanization	Irrigation	Extension	Equipment
PC – 1	-0.603	0.696*	0.170**	0.338	0.347
PC – 2	-1.867	0.514	0.042	-0.056	0.359
PC – 3	0.270	-0.118	0.023	0.406**	-0.531
PC – 4	-1.379	0.332	-0.009	-0.297	-0.133
PC – 5	-0.366	0.707*	0.094	0.400	-0.483
PC – 6	-0.466	-0.797**	-0.064	-0.538	-1.490
Sample size	9929	9929	9929	9929	9929

Source: Authors' estimations. Asterisks indicate statistical significance *10% **5% ***1%.

Appendix: Agroclimatic similarity indicators

Following Takeshima & Liu (2020), we generate AS indices, $\sigma_{i.R}$, for household i with respect to specific research locations, R as,

$$\sigma_{i.R,k} = -\left|\theta_i^k - \theta_R^k\right|. \quad (5)$$

θ_i^k and θ_R^k are the *k*-th principal component (PC) of agroclimatic parameters θ in areas where household i and *R* are located, respectively, and $\left|\theta_i^k - \theta_R^k\right|$ are absolute deviations. An increase in $\sigma_{i.R,k}$ indicates the increase in AS in terms of *k*-th PC. An AS index for farm household i with respect to *k*-th PC (σ_{ik}) is,

$$\sigma_{ik} = \max_B \sigma_{i,B,k}. \quad (6)$$

Thus, σ_{ik} is the AS with the most similar agricultural R&D locations for *i*, in terms of *k*-the PC of agroclimatic variables.

As is described in the descriptive statistics section, we use 6 PCs (therefore 6 different σ_{ik} variables), since 6 PCs explain a sufficiently large share of the overall variations in agroclimatic conditions (Table A2). We estimate the models separately using σ_{ik} for each of 6 PCs to check the robustness of the results.

Table A1. Principal components coefficients for each agroclimatic variable

Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7	PC 8	PC 9	PC 10	Unexplained
Rainfall	-0.434	-0.177	0.006	-0.141	0.107	-0.087	0.059	0.036	-0.045	0.060	0.097
Temperature	-0.053	-0.156	0.163	0.549	-0.387	0.142	-0.119	0.371	0.446	0.153	0.026
Drought index	0.307	0.263	-0.100	0.060	-0.053	0.094	-0.199	-0.440	0.032	0.374	0.136
Wind	0.384	0.049	0.101	-0.058	0.129	-0.053	0.433	0.106	-0.171	-0.241	0.129
Solar radiation	0.437	0.170	0.024	0.102	-0.105	0.023	0.053	0.162	0.010	-0.254	0.062
Alkalinity	0.295	0.340	0.115	0.077	0.072	0.041	-0.139	0.101	-0.162	0.449	0.145
Organic contents	-0.292	0.202	0.152	0.084	0.285	-0.108	0.262	-0.310	0.255	0.335	0.154
Medium texture	-0.185	0.481	0.029	-0.121	-0.377	-0.065	0.035	-0.132	0.131	-0.180	0.019
Coarse texture	0.234	-0.491	0.086	-0.057	0.070	-0.089	0.110	0.060	-0.101	0.347	0.016
Fine texture	-0.091	0.103	-0.206	0.391	0.634	0.302	-0.309	0.108	-0.095	-0.179	0.007
Salinity	-0.020	0.076	0.629	0.027	0.115	0.044	-0.234	-0.176	0.051	-0.375	0.049
Sodicity	-0.002	-0.158	0.638	-0.047	-0.005	0.043	-0.187	-0.085	-0.248	0.117	0.060
Poor drainage	-0.142	0.259	0.217	0.320	0.100	0.056	0.604	0.213	-0.142	0.115	0.126
Excess drainage	0.277	-0.246	0.008	0.177	0.209	-0.128	0.197	-0.402	0.539	-0.167	0.070
Ruggedness	0.097	0.205	0.122	-0.463	0.325	-0.201	-0.146	0.494	0.482	0.121	0.021
River distance	0.008	-0.064	0.038	-0.356	-0.024	0.883	0.206	-0.037	0.187	0.046	0.002

Source: Author's estimations.

Table A2. Proportion of variations in agroclimatic variables explained by principal components

Principal component	Proportion of variations
Principal Component 1	0.254
Principal Component 2	0.421
Principal Component 3	0.542
Principal Component 4	0.626
Principal Component 5	0.695
Principal Component 6	0.755
Principal Component 7	0.809
Principal Component 8	0.856
Principal Component 9	0.895
Principal Component 10	0.930

Source: Author's estimations.

Table A3. Correlation coefficients among agroclimatic similarity indicators based on different principal components

	AS based on PC 1	AS based on PC 2	AS based on PC 3	AS based on PC 4	AS based on PC 5	AS based on PC 6
Ethiopia						
AS based on PC 1	1.000					
AS based on PC 2	0.116	1.000				
AS based on PC 3	0.202	0.052	1.000			
AS based on PC 4	0.073	-0.069	0.053	1.000		
AS based on PC 5	0.207	-0.045	0.109	0.364	1.000	
AS based on PC 6	-0.101	-0.026	0.085	0.062	0.178	1.000

Source: Author's estimations.

ALL IFPRI DISCUSSION PAPERS

All discussion papers are available **here**

They can be downloaded free of charge

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE
www.ifpri.org

IFPRI HEADQUARTERS
1201 Eye Street, NW
Washington, DC 20005 USA
Tel.: +1-202-862-5600
Fax: +1-202-862-5606
Email: ifpri@cgiar.org