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Contents

List of tables

Abstract

This paper aims to analyse the relationship between technology adoption and access to credit by farmers in Tanzania, with particular focus on spatial spillover effects on technology adoption. We examine new technology diffusion by farmers through their peers, and measure geographical proximity using farms' GIS localization data. Using the 2012-2013 Tanzanian Household Survey and a spatial lag probit model, we find evidence that farmers' access to finance leads to increased agricultural technology adoption, and that the spillover effect plays a role in this process. In addition, our results are robust over a 3-year period (i.e., 2008-2009, 2010-2011, and 2012-2013). Finally, evidence of the existence of spillover effects in the adoption of agricultural technology suggests that interactions between farmers who are "geographical neighbours" should be supported/exploited to achieve substantial efficiency and savings in new agricultural technology extension.

Keywords: Technology adoption, technology diffusion, agricultural credit, maize cultivation, sub-Saharan Africa.

1. Introduction

Harnessing the potential of Tanzania's agricultural sector is key to the country's sustainable growth and export promotion. A significant increase in agriculture productivity is needed not only to supply domestic demand, but also to tap into larger markets at regional and global levels. In addition to helping generate more growth from agriculture, increased productivity would also free up labour to be employed in other higher value-added activities. Productivity trends were positive in Tanzania over several decades but have declined in recent years.[1] While agriculture production rose by 3% on average between 1961 and 2015, it still represented only half of South Africa's production and remains low compared to average middle-income countries. Furthermore, it has declined since 2012, reaching a -15% low in 2015.

Relatively low agricultural productivity may be due to a number of factors, including low levels of mechanization, limited access to inputs and/or financing, poor quality of infrastructure, and insufficient innovation. Innovation is essential to bringing about a sustainable increase in productivity in Tanzania, which is low by international standards. As an illustration, Tanzania's agricultural total factor productivity (TFP) index decreased by 3% over the period 1962-2015, while it rose by 41% in Asian countries.[2] Investment in the adoption of new technologies in the sector can strengthen agricultural production in Tanzania. However, accomplishing such an aim will require strengthening financial inclusion for farmers to enable them not only to access credit but also to transact in a manner that is convenient and does not require undue time, effort, or expense.

Financial inclusion refers to all initiatives that make formal financial services available, accessible, and affordable to all segments of the population (African Development Bank, 2013), including farmers and agricultural workers. Farmers and agricultural workers have historically been excluded from the formal financial sector for various reasons primarily related to their education and economic background. Inadequate access to financial services mainly occurs in the agricultural sector, which employs a sizeable portion of Africa's labour force. The factors hindering access to financial services in the agricultural sector include high delivery costs, low farming profits, lack of access to banking technology, the necessity of collateral, low productivity, long distance to the source of credit, type of credit source, lack of education, and price risk (Etonihu et al, 2013).

In Tanzania, a significant part of the population remains excluded from access to financial services, especially those living in rural areas and working in the agricultural sector; 54% of the agricultural labour force is excluded from all formal and informal financial services (National Financial Inclusion Framework - NFIF, 2014).[3] Indeed, until recently, the Tanzanian financial system has not been particularly inclusive; it is small and dominated by the banking sector, which accounts for 71% of the financial sector's total assets (International Monetary Fund, 2016).

Credit guarantee schemes have been designed and established to increase credit availability to support agriculture, given its prominence in Tanzania's economy. These schemes have made and continue to make a significant contribution to the expansion of credit in Tanzania (FSDT, 2016). Four of these schemes are currently active in Tanzania: (a) Private Agricultural Sector Support, funded by the Danish International Development Agency; (b) Sustainable Agriculture Guarantee Fund, funded by a private bank, Rabobank; (c) Agricultural Credit Guarantee, funded by Alliance for a Green Revolution in Africa, OPEC Fund for International Development, and Kilimo Trust; and (d) Cooperative and Rural Development Bank Guarantee, funded by African Development Bank and United States Agency for International Development and focused exclusively on agriculture (FSDT, 2016).

Because financial services are evolving in rural areas of Tanzania, their impact on the agricultural sector must be comprehensively assessed to support financial inclusion policies. The literature highlights the fact that inadequate access to formal financial services, including agricultural credit, impedes the adoption of new technologies and productivity (Giné and Yang, 2009; Meyer, 2015; Ogada et al, 2014).

While extensive work exists on credit impact on technology adoption and productivity (Abate et al, 2016; Duflo et al, 2006; Kumar et al, 2020), the role of a spillover effect induced by geographical proximity among farmers warrants further investigation. Indeed, two compelling questions are: (a) Is there a neighbourhood effect (i.e., a "contagion effect") in the adoption of new technologies? and (b) What is the role of the 'neighbourhood effect' in the impact of access to credit on technology adoption in agriculture? Against this backdrop, this paper aims to explore the relationship between technology adoption and credit access in Tanzania, while highlighting the role of a spillover effect induced by geographical proximity among farmers.

The choice of Tanzania as our subject is justified for two primary reasons. First, Tanzania has a National Financial Inclusion Framework, which aims to address obstacles to financial inclusion by designing, monitoring, and evaluating necessary policies and actions. Such a framework is important as it serves to put the results of the analysis and related policy actions into perspective. Second, while it focuses on the most recent household survey available (2012-2013), the analysis also takes advantage of structured data to offer new insights into the dynamics of farmers' behaviour over a three-year period (i.e., 2008-2009, 2010-2011, and 2012-2013). Furthermore, this study is relevant for several reasons: (a) The role of spillover effects in the relationship between access to credit and technology adoption, especially in the case of Tanzania, has not been extensively investigated; (b) this research improves the identification of neighbourhood effects on technology adoption; indeed, neglecting the role of neighbourhood effects could produce an under-estimation of the effect of financial inclusion on technology adoption; and (c) this research is policy-relevant because improving our understanding of the relationship between financial inclusion and technology adoption is helpful in designing sound policies and achieving better value for money/return on investments in their implementation.

2. Literature review

This research aims to contribute to the literature on technology adoption in the agriculture sector (Etonihu et al, 2013; Giné and Yang, 2009; Krishman and Patnam, 2014; Kumar et al, 2020; Manyong et al, 2005; Meyer, 2015; Nakano et al, 2018; Nwaru, 2004; 2006; Obwona, 2002; Ogada et al, 2014).To this end, it incorporates two strands of the literature: (a) The impact of access to finance on the adoption of agricultural technology; and (b) The role of peer interaction among farmers in the diffusion of technology.

A growing body of literature examines the drivers of technology adoption in the agriculture sector. Nakano et al (2018) showed that agricultural technology adoption in Tanzania increased yields of farmers from 3.1 tons per hectare to 5.3 tons per hectare, while the yield of ordinary farmers increased from 2.6 tons per hectare to 3.7 tons per hectare. Similarly, Kassie et al (2011) found that in Uganda, farmers' use of improved seeds has the potential to increase their crop income in the range of US$ 130 to US$ 254 and decrease the incidence of poverty by 7%-9%.

The literature highlights three key factors that prevent the adoption of agricultural technology, such as fertilizers and pesticides (Duflo et al, 2006); they are: (a) Using agricultural technology can lead to lower returns on average than expected, depending on some characteristics of a given plot of land; (b) using technology can generate higher returns, but farmers are either unaware of it or do not know how to make use of the technology; and (c) using technology can generate higher returns, and farmers know how to use it, but do not have the financial resources to invest in it.

While no consensus has emerged in the empirical analysis of which factors are most relevant to explaining the adoption of agricultural technology, a set of variables appears to play a pivotal role. The variables include access to finance and markets and the provision of subsidies, literacy, and trade (Abate et al, 2016; Kumar et al, 2020; Nakano and Magezi, 2020; Porteous, 2020; Nakano et al, 2018; Zhang et al, 2020).

Abate et al (2016) analysed the impact of rural finance on the adoption of agricultural technology (i.e., fertilizers and improved seeds) using a sample of 817 farm households in rural Ethiopia. The empirical analysis carried out using propensity score methodology suggests a positive and significant impact of access to finance on the adoption and use of agricultural technology. This result is consistent with Duflo et al.'s (2006) findings in Kenya using randomized field experiments, which highlight the role of access to financial resources to purchase fertilizer as an important determinant of its use. This result is also in line with the findings of Kumar et al (2020) in the case of Nepal. In this study, the author used seemingly unrelated regressions to identify the determinants of the adoption of specific technologies and practices. In contrast, Nakano and Magezi (2020), using a randomized control trial on a sample of Tanzanian households, showed that access to credit did not significantly affect the use of chemical fertilizers or productivity. A potential explanation suggested by Nakano and Magezi (2020) is that other factors such as access to irrigation play a significant role. Furthermore, the marginal use of fertilizer might be lower among farmers with better access to irrigation. Other factors such as market access, literacy, and trade costs and membership in a cooperative affect the probability of adopting agricultural technology (Kumar et al, 2020; Porteous, 2020; Zhang et al, 2020).

The role of social interaction has been cited as a determinant of access to financial services and the adoption of new technology. Manski (1993) advanced three hypotheses based on three types of effects—endogenous, contextual, and correlated—that might explain the impact of group membership on an individual's behaviour. First, endogenous effects reflect the idea that individual behaviour impacts group behaviour while group behaviour affects individual behaviour. These reciprocal effects are the result of mimicking mechanisms or social conditioning. The endogenous spillover effect can evolve in two directions. For example, the adoption of a technology by a farmer can: lead neighbouring farmers to adopt the technology as well (this refers to a strategic complement); or lead neighbouring farmers who have adopted the technology before to give up the technology (this refers to strategic substitute). Second, contextual effects reflect the idea that an individual's behaviour can be directly influenced by the exogenous characteristics of their group and by those of individual group members. Third, correlated effects indicate that individuals within a group behave in a similar fashion because they tend to have similar characteristics or face similar political, institutional, or environmental conditions. An array of studies has investigated the role of social interactions in technology adoption (e.g., Conley and Udry, 2010; Duflo et al, 2006; Foster and Rosenzweig, 1995), the diffusion of information (Banerjee et al, 2013; van den Broeck and Dercon, 2011) and risk sharing (de Weerdt and Dercon, 2006; de Weerdt and Fafchamps, 2011; Fafchamps and Gubert, 2007). Most of these studies found that social networks or peer influences had a powerful effect on behaviour (Ostrom, 2000), including technology adoption.

To date, few studies have explored the spatial (i.e., geographical) dimension of peer interactions in technology adoption, despite its importance to agriculture. Krishman and Patnam (2014) determined that learning from adopting neighbours demonstrated greater sway in promoting the adoption of fertilizer and improved seed varieties in Ethiopia than learning from agricultural extension services that provided farmer education on agricultural practices and new methods of cultivation. Krishman and Patnam (2014) constructed spatial neighbours matrix based on 1 km distance from each surveyed household and estimated a spatial lag probit model. Analysis by Kumar et al (2020) carried out from multinomial logit suggests that adoption of improved practices in Nepal increased when farmers obtained information from informal sources, including neighbouring farmers, family, and friends. In Tanzania, specifically, Nakano et al (2018) found that being a residential neighbour, which they measured with the inverse squared distance from each ordinary farmer's plot, was a key factor in the technology diffusion process in rice farming. They argued that farmer-to-farmer extension programmes for smallholders in Sub-Saharan Africa was a cost-effective alternative to the conventional farmer training approach.

We contribute to the literature on this topic by investigating the pattern of technology adoption in maize farming in Tanzania, considering financial inclusion and neighbouring interactions. Our research seeks to investigate the spatial interdependence at the individual farmer scale. We take advantage of GIS data to improve farm localization, which facilitates the identification of geographical patterns. Conducting advanced analysis with spatial econometrics also allows us to distinguish the direct impact of each explanatory variable and its induced spillover effects.

3. Theoretical and conceptual framework

Spatial diffusion is related to the first law of geography, that: "Everything is related to everything else, but near things are more related than distant things" (Tobler, 1970: 236). Geographical proximity often implies cultural similarity, social proximity, and economic interdependencies. Therefore, objectively, "something" e.g., ideas or technology) spreads by contagion from a point in the closest area rather than to remote areas from the place of emergence. Spatial autocorrelation is likely to exist in our study given that the adoption decision process is "an information-seeking and information-processing activity, where an individual is motivated to reduce uncertainty about the advantages and disadvantages of an innovation." Upon introduction, a new technology can either be adopted, if found to be beneficial and profitable relative to existing alternatives, or rejected, if found unprofitable (Dinar and Yaron, 1992). Based on the decision process described earlier, it is likely that as ‘the distance to technology’ (i.e., the distance from and contiguity to an area where the innovation is implemented) decreases, the information gap regarding the innovation’s profitability and adoption risks also decreases. Mobile technology (e.g., an information platform such as AgriTV) can also address this type of gap. Mobile technology allows information sharing without proximity, which can play a role in technology adoption and use. However, farmers who see firsthand the positive experience (results) of technology adoption of neighbouring farmers have a stronger incentive to adopt the technology than when simply receiving information (in a training or through a mobile platform).

Theoretically, perfect information is essential for efficiency in resource allocation, as it contributes to making informed choices and efficiently using resources. Moreover, knowledge of other people’s experiences can diminish uncertainty in technology adoption. Therefore, we can state that "distance to technology" can strongly affect technology adoption and diffusion by reducing transaction costs in information and experience seeking.

Information and experience seeking include both the ability to employ the technology and the funding necessary to acquire it. This argues for the presence of an endogenous spillover effect, according to which an individual’s behaviour is influenced by the behaviour of their neighbours. In other words, a given farmer’s adoption of a technology will lead their neighbours to adopt the same technology. Endogenous spillover effects can lead to the expansion of a good or bad technology or practice. However, if the technology or practice does not produce the expected effects, it is very likely that it will be abandoned in the short to medium-term due to the same mechanisms.

It is also likely that the characteristics of farmers and their land affect the diffusion process, a principle that argues for the presence of contextual (exogenous) effects, according to which similar behaviours are observed among individuals when the exogenous characteristics of the group are similar. Our study focuses on investigating the endogenous spillover effects, grounded by a contagion/mimicking effect hypothesis, to test whether spatial patterns affect the adoption of each technology tested (i.e., organic and inorganic fertilizers). Endogenous spillover effects cannot explain, theoretically, how the adoption of one technology can influence the adoption of another technology if we distinguish single (e.g., a fertilizer) versus package (e.g., fertilizer, improved seed variety, and good management practices) adoption.

In Africa, the agricultural methods used are ancestral. The introduction of new, more effective techniques to increase yields and diversify production face multiple barriers. Indeed, rural areas of Africa are characterized by low levels of education and strong peer influence on individual decisions. When a farmer adopts a new technology that increases production, the closest farmers perceive that adopting the technology themselves likewise signals their future productivity. The closer in proximity two pieces of land are, and the more accurate the shared information is, the more accelerated the diffusion of the technology. However, only farmers who are in the same contextual framework and have access to financial resources will be able to adopt some technologies. Indeed, without savings or access to formal and informal financial systems, farmers remain unable to adopt some new technologies. While other forms of distancing—including social and economic—could apply, data limitations prevent us from analysing them.

4. Econometric model

Technology adoption and spillover effects

We analyse the diffusion of a given production technology *k* among farmers. Thus, we want to determine whether the adoption of this technology by a farmer will have a positive influence on their neighbours deciding to adopt the technology. According to LeSage (2014), in such a context, a spatial autoregressive regression model (SAR) is the most appropriate. A SAR model allows the identification of endogenous effects (i.e., spatially lagged endogenous variables). The model to be estimated can be written as follows:

$$T_J = \rho_{1j} W T_J + \alpha_1 FI_i + \beta_{1k} X_k + \epsilon_J \tag{1}$$

where T_J is the technology *j*, FI_i is the access to finance (access to credit here) by farmer *i*, X_k represents the other explanatory variables (the characteristics of the farmer and their vicinity), and ρ_{1j} is the spatial autocorrelation coefficient of technology *j* (objective 1). $W T_J$ is the spatially lagged endogenous variable. Each element w_{ij} (inverse distance between the farmers) of the weight factor *W*, measures the intensity of the links between farmers *i* and *j* and is obviously specific to each peer type. The closer two farmers are in terms of distance, the higher the w_{ij} will be. As emphasized by LeSage (2014), *W* catches global spillovers, allowing all famers to be connected. While spillover effects decrease with the distance between farms, more weight is given to the nearest farmers. W is symmetric and normalized by dividing each element by the sum of the line.[4] Therefore, the relationship between two farmers depends on the relative distance between them and not on the absolute distance. Algebraically, an element w_{ij} of the geographic distance weighting matrix takes the following form:

$$w_{ij} = \begin{cases} \dfrac{1/d_{ij}}{\sum_j 1/d_{ij}}, & for\ i \neq j \\ 0, & for\ i = j \end{cases}$$

where d_{ij} is the Euclidean distance between farmers *i* and *j*. If the spatial autocorrelation coefficient is significant and positive for a given technology, then we can conclude that there is a diffusion of this production technology among farmers.

Thus, in adopting this technology, there is synergy between farmers, who consider the experience of their neighbours in the use of this technology in their production process.

The presence of the spatially lagged-dependent variable in the equation creates an endogeneity problem generated through the simultaneity relationship between WT_j and T_j . To control for this bias, we use a hierarchical Bayesian approach introduced by LeSage (2000), as it allows both spatial dependences and general spatial heteroscedasticity to be treated simultaneously. The approach consists in deriving a reduced form of Equation 1:

$$I - \rho_{1j} W) \, T_J = \alpha_1 FI_i + \beta_{1k} \textstyle\sum_{i \neq j} X_{ik} + \epsilon_{J,i}$$

$$T_J = (I - \rho_{1j} W) \; ^{-} [\alpha_1 FI_i + \beta_{1k} \textstyle\sum_{i \neq j} X_{ik} + \epsilon_{J,i}]$$

I is an identity matrix. As shown by LeSage and Pace (2009), the spatial multiplier matrix can be decomposed as follows:

$$(I - \rho_{1j} W)^{-1} = I + \rho_{1j} W + \rho_{1j}{}^2 W^2 + \rho_{1j}{}^3 W^3 + \cdots + \rho_{1j}{}^n$$

Since the non-diagonal elements of the first matrix term on the right-hand side (the identity matrix I) are zero, this term represents a direct effect of a change in X (given explanatory variable) only. Conversely, since the diagonal elements of the second matrix term on the right-hand side ($\rho_{1j} W$) were assumed to be zero (see below), this term represents an indirect effect of a change in *X* only. In addition, as stipulated by Elhorst (2014) “since *W* is taken to the power 1 here, this indirect effect is limited to first-order neighbours only; i.e., the units that belong to the neighbourhood set of every spatial unit. All other terms on the right-hand side represent second- and higher-order direct and indirect effects. Higher order direct effects arise because of feedback effects; i.e., impacts passing through neighbouring units and back to the unit itself.

Data

To conduct this study, we use a GIS database of Tanzanian farmers. This database is compiled from the World Bank household survey project, entitled the Living Standards Measurement Study–Integrated Surveys on Agriculture (LSMS-ISA). The LSMS-ISA aims to build a nationally representative panel survey database with a multi-topic approach designed to improve understanding of the links between agriculture, socio-economic status, and non-farm income activities. Indeed, in our dataset, all the farmers’ production processes (i.e., input and output) are described, along with relevant household characteristics (e.g., age, sex, education, and marital status). We focus the analysis on the 2012-2013 waves and use the waves of 2008-2009 and 2010-2011 for robustness checks. These datasets contain reliable data on farmers’ access to and use of financial services. We are aware of the existence of the wave from 2014-2015; however, in the 2014-2015 LSMS, the geolocation of households is not accessible to the public. These data constraints precluded us from replicating the spatial models on this wave.

The variables used in the study are described in Table 1. We focus on maize, the main crop grown by farmers in the sample under scrutiny. Maize accounts for 80% of the total cereal production in the sample. All variables related to the technology adoption (pesticide, organic fertilizer, inorganic fertilizer, etc) are measured only on plots intended for maize production. Financial inclusion is the delivery of financial services and products at an affordable cost to all individuals and businesses regardless of income level. In this study, financial access is measured with the variable access to credit to finance the purchase of agricultural inputs. We focus on three innovative technologies: the use of both inorganic and organic fertilizers and the use of pesticides. We have created a fourth category (mixed technology), which brings together all farmers who use at least two production technologies. The choice of these specific technologies is dictated by data availability. Assuming that a household's production decisions in any time period is also determined by a household's socioeconomic characteristics, including the head of household's age and sex and household size and education level, we include these variables as control variables. We use the localization of the farmers through the GIS database to define a neighbour matrix.

Table 1: Definition of variables

Variable	Definition	Unit
Credit	1 if the individual farmer has access to credit over the past 12 months and uses it to purchase agricultural inputs, 0 otherwise	Binary
Organic fertilizer	1 if organic fertilizers are used on main plot, 0 otherwise	Binary
Inorganic fertilizer	1 if inorganic fertilizers are used on main plot, 0 otherwise	Binary
Pesticides	1 if pesticides are used on main plot, 0 otherwise	Binary
Mixed technology	1 if the farmer uses more than one technology, 0 otherwise	Binary
Age head of HH	Age in completed years of individual farmer	Year
Gender	1 if the individual farmer is male, 0 otherwise	Binary
Household size	Total number of household members	Number
Literate	1 if the individual farmer can read/write in Kiswahili, English, or any other language, 0 otherwise	Binary

Detailed statistics are included in Table 2: Summary statistics for Tanzanian individuals farmers and Table 3. The combined surveys have 1,712 individual farmers. They are primarily small farmers, given that the average farm size was less than 1ha for about 74% in 2012 (respectively, 73% of farms in 2008; 75% in 2010).

The summary statistics for this sample indicate that, on average, 8.41% of individual farmers have access to credit. This access has grown steadily in recent years, and the average value of credit borrowed amounts to between US$29.710 and US$30. About 20% of this amount is devoted to agriculture and business inputs, while 25.69% goes to fulfilling subsistence needs, 20.83% to investment in education and health, and the remainder to other types of spending, including buying or building a dwelling. We note that, in Tanzania, individual farmers are typically male (76-80%), married (77%), literate (72%-74%) and, on average, 47 years old. The average household is composed of five people. Overall, Tanzanian farmers harvest an average of 612.33kg of maize from an average area of 0.6638 hectares. We note that the quantity of maize harvested has increased along with the number of hectares farmed over the years. The production of maize value is an average of over US$66. Most Tanzanian farmers intercrop maize with other crops (54.43%) and use different agricultural technologies on their main plots. For example, approximately 20%, 22%, and 31% use organic or inorganic fertilizers and improved seeds, respectively, while less than 10% use pesticides. The amount of organic fertilizer used is, on average, higher than the amount of inorganic fertilizers used. In fact, an average of 206.15kg of organic fertilizer is used on the main plot, compared to 47kg of inorganic fertilizer. In addition, around 16% of individual Tanzanian farmers use only organic fertilizers on their main plots, while 14% use only inorganic fertilizers, and 5.6% use both.

Table 2: Summary statistics for individual Tanzanian farmers

	2008	2010	2012	Pooled
Financial inclusion indicator				
Access to credit (%)	0.0663	0.0769	0.1055	0.0841
Amount of credit (US$)	11.48	15.47	56.43	29.71
Purchase agricultural inputs (%)	0.1750	0.2000	0.2173	0.2013
Other business inputs (%)	0.2000	0.1428	0.2173	0.1944
Subsistence needs (%)	0.3000	0.3142	0.2028	0.2569
Medical cost, school fees (%)	0.225	0.2285	0.1884	0.2083
Buy/build dwelling (%)	0.0500	0.0285	0.0434	0.0416
Other (%)	0.5000	0.0857	0.1304	0.0972
Household profit				
Age (year)	46.49	43.08	47.48	46.95
Gender: 1-Male (%)	0.7579	0.7604	0.7981	0.7740
Married (%)	0.7613	0.7604	0.7767	0.7670
Household size	5.1714	5.6307	5.6636	5.4829
Literate (%)	0.7445	0.7296	0.7247	0.7329
Productivity and technology adoption				
Quantity harvested (kg)	593.7944	646.9516	605.34	612.33
Area harvested (hectare)	0.6163	0.6470	0.7221	0.6638

Estimated value of the harvested crop (US$)	44.37	60.12	92.26	66.84
Intercropped crop	0.6517	0.6395	0.3792	0.5443
Organic fertilizer: 1-yes (%)	0.2039	0.2153	0.2262	0.2155
Inorganic fertilizer: 1-yes (%)	0.1691	0.2263	0.2048	0.1980
Pesticides: 1-yes (%)	0.0928	0.1076	0.0917	0.0963
Improved seeds: 1-yes (%)	0.1509	0.5465	0.4189	0.3067
Observation	603	455	654	1,712

Table 3: Organic and inorganic fertilizers on the main plot

	2008	2010	2012	Pooled
Quantity of organic fertilizer (kg)	255.69	177.37	180.50	206.15
Quantity of inorganic fertilizer (kg)	83.892	77.914	21.391	47.892
Only organic fertilizer: 1-yes	0.1542	0.1428	0.1758	0.1594
Only inorganic fertilizer: 1-yes	0.1194	0.1538	0.1544	0.1419
Both organic and inorganic: 1-yes	0.0497	0.0725	0.0504	0.0560
Observation	603	455	654	1,712

5. Results and discussion

Financial access, technology adoption and spillover effects

Table 4: Spatial autoregressive regression (SAR) model of technology adoption, financial access, and spillovers effects models

	2012			
	OF	INF	P	Mix
Credit	0.1641	0.7652*	0.6709*	0.8774**
	(0.3908)	(0.4042)	(0.3606)	(0.3696)
Gender	0.2906*	0.0085	0.1203	0.0420
	(0.1634)	(0.1800)	(0.2103)	(0.1855)
Age head of HH	0.0114***	0.0004	0.0007	0.0155***
	(0.0039)	(0.0043)	(0.0055)	(0.0050)
Household size	0.0785***	0.0373*	0.0280	0.0151
	(0.0179)	(0.0224)	(0.0223)	(0.0196)
Literate	0.3324**	0.6091***	0.0159	0.8707***
	(0.1489)	(0.1668)	(0.1920)	(0.2112)
Inorganic fertilizers	0.0330		0.7213***	
	(0.1365)		(0.1525)	
Pesticides	0.2394	0.9367***		
	(0.1795)	(0.1987)		
Organic fertilizers		0.0202	0.2636*	
		(0.1463)	(0.1543)	
Cons.	-2.1184***	0.8129**	-1.5714***	-2.4907***
	(0.2878)	(0.3230)	(0.3877)	(0.3808)
rho	0.2291**	0.6459***	0.2981***	0.3377***
	(0.0892)	(0.0413)	(0.1048)	(0.0921)

OF: Organic Fertilizer; INF: Inorganic Fertilizer; P: Pesticides; Mix: mixed technology, more than one technology
Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results of spatial lag probit models for technology adoption are presented in Table 4. The presence of spatial interactions in technology adoption is confirmed by a significant and positive value at 5%. This result suggests that in Tanzania, a farmer's adoption of new technology in maize production influences whether their neighbours adopt the technology; thus, there is diffusion of this production technology among farmers. Specifically, a geographical (i.e., spatially close) neighbour deciding to adopt new technology influences nearby farmers' technology adoption. This result is in line with the results of Nakano et al (2018), whose study documents the existence of spillover effects in the adoption of agricultural technologies for rice farming in Tanzania. The value indicates that the effect is greater for inorganic fertilizer adoption than for other technologies (i.e., organic fertilizer, pesticides or mixed technology). This can be explained by the different facilities (loans, provision of fertilizers and payment at harvest, etc) put in place for the adoption of inorganic fertilizers, especially for cash crops. The coefficient is about 0.64 for inorganic fertilizer, 0.29 for pesticides, and 0.23 for organic fertilizer.

According to LeSage and Pace (2009), in the presence of spatial interactions, the impact of the explanatory variables on the dependent variable can be parsed into direct and indirect effects. The direct effect of explanatory variables on the decision to adopt a technology measures the impact of a change in the explanatory variable of farmer *i* on their decision to adopt the technology. The indirect effect measures the impact of a change in the explanatory variable of farmer *i* on whether all other farmers decide to adopt the technology. Therefore, indirect effects are global spillovers because they affect all farmers, not just those in proximity. However, indirect effects pertain more to farmer *i*'s vicinity because they decrease with the distance between two farms. Therefore, we can determine the impact of financial inclusion not only on an individual farmer's decision to adopt a technology but also on neighbouring farmers' decisions to adopt. The total marginal effects are presented in Table 5 (see full results in Appendix 2).

Table 5: Direct and indirect marginal effect of credit access on technology adoption in 2012

Agricultural technology	Marginal effect	Estimated effect of credit access
Organic Fertilizers	Direct Effects	0.0444
	Indirect Effects	0.0135
	Total Effects	0.0580
Inorganic Fertilizers	Direct Effects	0.1670*
	Indirect Effects	0.2217*
	Total Effects	0.3888*
Pesticides	Direct Effects	0.0965*
	Indirect Effects	0.0344
	Total Effects	0.1310*
Mix Technology	Direct Effects	0.1352**
	Indirect Effects	0.0552*
	Total Effects	0.1905**

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We find no marginal effect of credit access on organic fertilizer adoption. This result is plausible, as organic fertilizers are, in most cases, often composted by the farmers themselves. Concerning inorganic fertilizer adoption, we find significant marginal direct and indirect effects of credit. The indirect effect of credit on the probability of technology adoption is as important as the direct effect (i.e., the effect on one farmer's adoption). More precisely, access to credit by farmer *i* will increase not only their probability of adopting inorganic fertilizer by 16.7% (direct effect) but also the probability of neighbouring farmers also adopting inorganic fertilizer by 22.2% (indirect effect). Therefore, the total effect of access to credit is 38.9%. Ignoring the spatial aspect in this analysis would have led to underestimating the effect of access to credit.

We find a significant direct effect of credit access on pesticide adoption. We do not find evidence of an indirect effect of credit access on pesticide adoption. We also find that access to credit has a significant impact on the probability of a farmer adopting more than one technology, or "mixed technology". The result indicates that access to credit has a favourable impact on inorganic fertilizer adoption and a marginally favourable impact on pesticide adoption for maize crops. For the other explanatory variables involved in technology adoption, we find robust results for the impact of household size on organic and inorganic fertilizer adoption, and the impact of literacy on the adoption of organic fertilizer, inorganic fertilizer, and mixed technology.

These findings are consistent with the existing literature on a couple of key points. First, alleviating the constraints on farmers' access to funding is essential to enhancing the adoption of agricultural technology. Specifically, the results echo those of Duflo et al (2006), Abate et al (2016), and Kumar et al (2020). While Duflo et al (2006) emphasized the ability to finance the purchase of fertilizer as an important determinant of its use, Abate et al (2016) showed that the impact of financing is higher when it is obtained from a cooperative. However, the results contrast with those of Nakano and Magezi (2020), who did not find any significant impact of access to credit on the use of chemical fertilizers. Although their study also focused on Tanzanian farmers, three distinctive factors could explain the difference in the findings: (a) Our study focuses on maize crops, while their study focused on rice; (b) Nakano and Magezi (2020) focused on microcredit, while our study shows in the data section that the amount of credit received by the farmer is high. Thus, we ascribe the significant impact observed in 2012 survey waves to the higher amount of credit received relative to the previous waves; and (c) our study accounts for both direct and indirect effects of credit access, controlling *de facto* for a potential social learning effect. Furthermore, our analysis reveals that the size of the household and degree of literacy significantly increase the probability of a farmer adopting agricultural technology, including inorganic fertilizers and pesticides. The latter finding corroborates those of Nakano et al (2018), according to which the probability of adopting agricultural technology is higher for trained farmers than for untrained farmers.

Robustness check

We estimate the models on the 2008-2009 and 2010-2011 waves to check the robustness of the key findings.

The presence of spatial interactions in technology adoption is confirmed at 5% in the waves of 2008-2009 and 2010-2011, which confirms our findings on technology diffusion among farmers.

The results on the 2008-2009 and 2010-2011 waves confirm the absence of an effect of credit access on organic fertilizer adoption. Credit had significant marginal direct and indirect effects on inorganic fertilizer adoption in 2008, but not in 2010. Its effects on pesticide adoption are not significant. One reason for differences in the effects of credit on inorganic fertilizer and pesticide adoption could be the variation in credit amounts over the years. Indeed, in 2008 and 2010, the mean amount of credit available for farmers to purchase agricultural inputs was Tsh208,714 and Tsh186,285, respectively, while in 2012, the mean credit was Tsh1,025,440. Thus, in 2008 and 2012, farmers had greater means with which to purchase inorganic fertilizer and pesticides but less in 2010. The probability of adopting a technology seems to be an issue of credit amount rather than of credit access. Due to data constraints (i.e., the low number of observations in the databases over the years for the amount of credit available for agricultural input purchases), we are unable to verify this conclusion/supposition.

6. Conclusion

In this study, we examine the relationship between technology adoption and credit access of farmers in Tanzania. We test specifically the role of farmers' diffusion of new technology through their peers and focus on their geographical proximity using farms' GIS localization data. We assume that geographical proximity increases the availability of accurate information and accelerates technology diffusion. The results of the spatial lag probit models used support the hypothesis that financial access leads to increased agricultural technology adoption, and that the spillover effect has an impact on this process.

We find that improved access to credit leads to greater spillover effects in the adoption of inorganic fertilizers and pesticides. As farmers' level of credit increases, their purchasing power and the probability of their adopting new agricultural technology, such as inorganic fertilizer, also increases. Therefore, improving financial access to agricultural technology, including fertilizers and pesticides, is relevant to policy. The existence of spillovers in the adoption of agricultural technology suggests that a typical policy aimed at easing access to inorganic fertilizers or pesticides could generate an impact that goes well beyond the original target, leading to increased efficiency and lower cost. We conclude that by promoting inorganic fertilizers (through credit facilitation, for example) to a small set of farmers, the government could indeed achieve increased acceptance and adhesion and higher agriculture productivity thanks to spillover effects.

Notes

1 Gross agriculture production is measured as the total value of crop and animal production, using constant 2004-2006 global average farmgate prices in US$1,000 purchasing-power-parity dollars and are drawn from the US Department of Agriculture Economic Research Service, whose latest release is from November 2019.
2 TFP can be seen as a proxy of innovation in agriculture.
3 The National Financial Inclusion Framework report (Tanzania).
4 This symmetric matrix defines, for each observation (row), locations that belong to its neighbourhood set as non-zero elements.

References

Abate G.T., S. Rashid, C. Borzaga and K. Getnet. 2016. “Rural finance and agricultural technology adoption in Ethiopia: Does the institutional design of lending organizations matter? *World Development*, 84: 235-253.

Banerjee, A., A.G. Chandrasekhar, E. Duflo and M.O. Jackson. 2013. “The diffusion of microfinance”. *Science*, 341(6144).

Conley, T. and C. Udry. 2010. “Learning about a new technology: Pineapple in Ghana”. *American Economic Review*, 100: 35-69.

de Weerdt, J. and M. Fafchamps. 2011. “Social identity and the formation of health insurance networks”. *Journal of Development Studies*, 47: 1152-1177.

de Weerdt, J. and S. Dercon. 2006. “Risk-sharing networks and insurance against illness”. *Journal of Development Economics*, 81: 337-356.

Dinar, A. and D. Yaron. 1992. “Adoption and abandonment of irrigation technologies”. In A. Dinar and D. Zilberman, eds., *Economics of water resources: The contributions of Dan Yaron.*" Natural Resource Management and Policy. Boston, MA: Springer US. https://doi.org/10.1007/978-1-4615-0899-1_13.

Duflo, E., M. Kremer and J. Robinson. 2006. "Why don’t farmers use fertilizer? Evidence from field experiments in Eastern Kenya." Unpublished manuscript.

Elhorst, J.P. 2014. “Spatial econometrics: From cross-sectional data to spatial panels”. *Springer Briefs in Regional Science*. New York: Springer.

Etonihu, K., S. Rahman and S. Usman. 2013. “Determinants of access to agricultural credit among crop farmers in a farming community of Nasarawa State, Nigeria”. *Journal of Development Agricultural Economics*, 5: 192-196.

Fafchamps, M. and F. Gubert. 2007. “The formation of risk sharing networks”. *Journal of Development Economics*, 83(2): 326-350.

Foster, A.D. and M.R. Rosenzweig. 1995. “Learning by doing and learning from others: Human capital and technical change in agriculture”. *Journal of Political Economy*, 103(6): 1176-1209.

FSDT. 2016. "Review of guarantee schemes in Tanzania." Financial Sector Deepening Trust.

Giné, X. and D. Yang. 2009. “Insurance, credit, and technology adoption: Field experimental evidence from Malawi”. *Journal of Development Economics*, 89: 1-11.

International Monetary Fund. 2016. "United Republic of Tanzania Selected Issues: Macrofinancial Issues (No. 16/255)." IMF country report. International Monetary Fund.

Kassie, M., B. Shiferaw and G. Muricho. 2011. “Agricultural technology, crop income, and poverty alleviation in Uganda”. *World Development*, 39(10): 1784-1795.

Krishman, P. and M. Patnam. 2014. “Neighbours and extension agents in Ethiopia: Who matters more for technology adoption? *American Journal of Agricultural Economics*, 96(1): 308-327.

Kumar, A., H. Takeshima, G. Thapa, N. Adhikari, S. Saroj, M. Karkee and P.K. Joshi. 2020. “Adoption and diffusion of improved technologies and production practices in agriculture: Insights from a donor-led intervention in Nepal”. *Land Use Policy*, 95: 104621.

LeSage, J.P. 2000. “Bayesian estimation of limited dependent variable spatial autoregressive models”. *Geographical Analysis*, 32(1): 19-35.

LeSage J.P., and R.K. Pace. 2009. *Introduction to spatial econometrics*. Boca Raton, FL: CRC Press Taylor and Francis.

LeSage, J.P. 2014. *What regional scientists need to know about spatial econometrics*. Rochester, NY: Social Science Research Network. Available at: http://papers.ssrn.com/sol3/Papers.cfm?abstractid = 2420725.

Manyong. V.M., A. Ikpi, J.K. Olayemi, S.A. Yusuf, B.T. Omonona, V. Okoruwa, and F.S. Idachaba. 2005. *Agriculture in Nigeria: Identifying opportunities for increased commercialization and investment*. Ibadan: IITA.

Manski, C.F. 1993. “Identification of endogenous social effects: The reflection problem”. *Review of Economic Studies*, 60(3): 531-42.

Meyer, R.L. 2015. "Financing agriculture and rural areas in Sub-Saharan Africa: Progress, challenges and the way forward." 10.13140/RG.2.1.4389.1688.

Nakano, Y. and E. Magezi. 2020. “The impact of microcredit on agricultural technology adoption and productivity: Evidence from randomized control trial in Tanzania”. *World Development*, 133: 104997.

Nakano, Y., W. Tsusaka, T. Aida, and V. Pede. 2018. “Is farmer-to-farmer extension effective? The impact of training on technology adoption and rice farming productivity in Tanzania”. *World Development*, 105: 336-351.

Nwaru, J.C., 2004. "Rural credit market and resource use in arable crop production in imo state of Nigeria." University of Agriculture, Umudike, Nigeria.

Obwona, M. 2006. *Determinants of Technical Efficiency Differentials amongst Small and Medium Scale Farmers in Uganda: A Case of Tobacco Growers.* African Economic Research Consortium Research, Paper 152.

Ogada, M.J., G. Mwabu and D. Muchai. 2014. “Farm technology adoption in Kenya: A simultaneous estimation of inorganic fertilizer and improved maize variety adoption decisions”. *Agricultural and Food Economics*, 2: 1-18.

Ostrom, E. 2000. “Collective action and the evolution of social norms”. *Journal of Economic Perspectives*, 14(3): 137-158.

Porteous, O. 2020. “Trade and agricultural technology adoption: Evidence from Africa”. *Journal of Development Economics*, 144: 102440.

Tobler, W.R. 1970. “A computer movie simulating urban growth in the Detroit region”. *Economic Geography*, 46: 234-240. Supplement: Proceedings. International Geographical Union. Commission on Quantitative Methods.

van den Broeck, K. and S. Dercon. 2011. “Information flows and social externalities in a Tanzanian banana growing village”. *Journal of Development Studies*, 47(2): 231-252.

Zhang, S., Z. Sun, W. Ma, V. Valentinov. 2020. “The effect of cooperative membership on agricultural technology adoption in Sichuan, China”. *China Economic Review*, 62: 101334.

Appendixes

Appendix 1: SAR of technology adoption, financial access, and spillovers effects models

	2008				2010				2012			
	OF	INF	P	Mix	OF	INF	P	Mix	OF	INF	P	Mix
Credit	0.1463	1.2029*	0.1631	0.5202	0.0610	0.29005	0.8412	0.6204	0.1641	0.7652*	0.6709*	0.8774**
	(0.4833)	(0.6173)	(0.5543)	(0.5180)	(0.5557)	(0.6586)	(0.5780)	(0.5548)	(0.3908)	(0.4042)	(0.3606)	(0.3696)
Gender	0.1078	0.1638	0.0043	0.1020	0.0591	0.14968	0.3455	0.1520	0.2906*	0.0085	0.1203	0.0420
	(0.1527)	(0.2087)	(0.2071)	(0.1876)	(0.1860)	(0.1858)	(0.2460)	(0.2265)	(0.1634)	(0.1800)	(0.2103)	(0.1855)
Age Head of HH	0.0066	0.0019	0.0029	0.0089	0.0088*	0.00089	0.0039	0.0098*	0.0114***	0.0004	0.0007	0.0155***
	(0.0041)	(0.0050)	(0.0056)	(0.0056)	(0.0051)	(0.0051)	(0.0062)	(0.0051)	(0.0039)	(0.0043)	(0.0055)	(0.0050)
Household Size	0.0995***	0.0282	0.0211	0.0090	0.0722***	0.07530**	0.0085	0.0574**	0.0785***	0.0373*	0.0280	0.0151
	(0.0216)	(0.0312)	(0.0328)	(0.0270)	(0.0213)	(0.0303)	(0.0298)	(0.0278)	(0.0179)	(0.0224)	(0.0223)	(0.0196)
Literate	0.1686	0.5492**	0.6363**	1.0990***	0.2983*	0.64238***	0.1686	0.5068**	0.3324**	0.6091***	0.0159	0.8707***
	(0.1550)	(0.2174)	(0.2544)	(0.3038)	(0.1784)	(0.2216)	(0.2317)	(0.2067)	(0.1489)	(0.1668)	(0.1920)	(0.2112)
Inorganic Fertilizers	0.1919		0.8118***		0.2709*		0.8455***		0.0330		0.7213***	
	(0.1603)		(0.1674)		(0.1602)		(0.1975)		(0.1365)		(0.1525)	
Pesticides	0.3755*	0.9741***			0.8635***	0.93188***			0.2394	0.9367***		
	(0.1933)	(0.2011)			(0.2033)	(0.2243)			(0.1795)	(0.1987)		
Organic Fertilizers		0.2213	0.2977			0.26522	0.8373***			0.0202	0.2636*	
		(0.1679)	(0.1840)			(0.1856)	(0.1859)			(0.1463)	(0.1543)	
Cons.	-1.5859***	-1.2317***	-1.8888***	-2.3259***	-1.8900***	0.61220	-1.7658***	-1.3673***	-2.1184***	0.8129**	-1.5714***	-2.4907***
	(0.2987)	(0.3904)	(0.4640)	(0.4633)	(0.3712)	(0.3975)	(0.4571)	(0.3786)	(0.2878)	(0.3230)	(0.3877)	(0.3808)
rho	0.3170***	0.6045***	0.2462**	0.4381***	0.2998***	0.59751***	0.3298***	0.4646***	0.2291**	0.6459***	0.2981***	0.3377***
	(0.0764)	(0.0440)	(0.1054)	(0.0981)	(0.0746)	(0.0546)	(0.1034)	(0.0773)	(0.0892)	(0.0413)	(0.1048)	(0.0921)

OF: Organic Fertilizer; INF: Inorganic Fertilizer; P: Pesticides; Mix: mixed technology, more than one technology

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix 2: Direct and indirect marginal effect of credit access and household characteristics on technology adoption

		Organic Fertilizers			Inorganic Fertilizers			Pesticides			Mix Technology		
		Direct Effects	Indirect Effects	Total Effects	Direct Effects	Indirect Effects	Total Effects	Direct Effects	Indirect Effects	Total Effects	Direct Effects	Indirect Effects	Total Effects
2008	Credit	0.0374	0.0172	0.0547	0.2089*	0.2185*	0.4275*	0.0213	0.0059	0.0273	0.0659	0.0429	0.1088
	Gender	0.0278	0.0112	0.0390	0.0296	0.0308	0.0604	0.0007	0.0001	0.0009	0.0134	0.0089	0.0224
	Age Head of HH	0.0017	0.0006	0.0023	0.0003	0.0003	0.0007	0.0004	0.0001	0.0005	0.0011	0.0007	0.0018
	Household Size	0.0255***	0.0105***	0.0361***	0.0048	0.0051	0.0099	0.0028	0.0009	0.0037	0.0011	0.0007	0.0018
	literate	0.0435	0.0177	0.0613	0.0958***	0.1008**	0.1967**	0.0871**	0.0252	0.1124**	0.1414***	0.0916**	0.2330***
	Inorganic Fertilizers	0.0492	0.0195	0.0687				0.1112***	0.0311**	0.1424***			
	Pesticides	0.0965*	0.0395*	0.1361*	0.1696***	0.1776***	0.3473***						
	Organic Fertilizers				0.0387	0.0407	0.0795	0.0406	0.0115	0.0522			
2010	Credit	0.0147	0.00576	0.0205	0.0668	0.0665	0.1334	0.1138	0.0473	0.1612	0.1193	0.0740	0.1934
	Gender	0.0151	0.0056	0.0208	0.0338	0.0358	0.0697	0.0467	0.0194	0.0661	0.0286	0.0187	0.0473
	Age Head of HH	0.0022*	0.0008	0.0030*	0.0001	0.0001	0.0003	0.0005	0.0002	0.0007	0.0018*	0.0011*	0.0030
	Household Size	0.0181***	0.0069***	0.0250***	0.0168***	0.0177***	0.0345***	0.0012	0.0004	0.0017	0.0108*	0.0069*	0.0177
	literate	0.0755*	0.0288	0.1043	0.1441***	0.1530***	0.2971***	0.0216	0.0101	0.0318	0.0959**	0.0613**	0.1573
	Inorganic Fertilizers	0.0681*	0.0257	0.0938*				0.1135***	0.0473***	0.1609***			
	Pesticides	0.2175***	0.0824***	0.2999***	0.2084***	0.2191***	0.4275***						
	Organic Fertilizers				0.0590	0.0627	0.1218	0.1125***	0.0472***	0.1597***			

Appendix 2 (Continued)

2012	Credit	0.0444	0.0135	0.0580	0.1670*	0.2217*	0.3888*	0,0965*	0,0344	0.1310*	0.1352**	0.0552*	0.1905**
	Gender	0.0792*	0.0242	0.1035*	0.0015	0.0023	0.0038	0,0169	0,0062	0.0231	0.0068	0.0027	0.0096
	Age Head of HH	0.0031***	0.0009*	0.0040***	0.0000	0.0001	0.0001	0,0000	0,0000	0.0001	0.0023***	0.0009**	0.0033***
	Household Size	0.0213***	0.0063**	0.0276***	0.0082	0.0109	0.0192	0,0039	0,0014	0.0054	0.0022	0.0009	0.0032
	literate	0.0904***	0.0268	0.1172**	0.1350***	0.1777***	0.3128***	-0,002	-0,000	0.0029	0.1351***	0.0554**	0.1905***
	Inorganic Fertilizers	0.0089	0.0024	0.0113				0,1026***	0,0374***	0.1400***			
	Pesticides	0.0654	0.0194	0.0848	0.2064***	0.2728***	0.4792***						
	Organic Fertilizers				0.0045	0.0056	0.0102	0,0372	0,0134	0.0507			

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