New Maize Variety Adoption in Mozambique: A Spatial Approach

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Abstract

Farmers in developing countries can dramatically improve their productivity by adopting new plant varieties. Yet, informational barriers often mean adoption rates remain low. In this study, we focus on how learning from others represents one means of removing informational barriers. We capture the effect of social learning through an explicitly spatial econometric model, applied to farm-level maize adoption rates in Mozambique. We find that social learning is significant, and explains the apparent clustering of adoption among farmers. Agencies interested in promoting variety adoption, therefore, would be well-served to leverage the strength of existing information networks, rather than imposing solutions that work against inter-farmer information flow.

Keywords: Rural development, social learning, spatial econometrics

Introduction

Adoption of new technologies is critically important to productivity growth in agriculture (Griliches 1960, 1957; Foster and Rosenzweig 1995; Conley and Udry 2001; Sunding and Zilberman 2001). This observation is particularly true in the case of new variety adoption by farmers in developing countries. Non-adoption can be due to technological barriers (Bandiera and Rasul 2006), policy limitations(Case 1991; Greiner and Gregg 2011), or simply a lack of information(Feder and O'Mara 1982; Zhao et al. 2003; Bandiera and Rasul 2006). Observed patterns of adoption clustering among neighbors, however, suggest the latter is likely to be dominant as technology and policy should apply equally to all. Indeed, information, or the lack thereof, is often found to be the most important factor limiting rural development(Banerjee 1992; Bikhchandani, Hirshleifer, and Welch 1992; Case, Rosen, and Hines 1993). In this paper, we investigate new variety adoption with a focus on information exchange among farmers.

Information can be acquired in a number of ways: through formal education, social media, trade organizations, or simply by imitating others. Perhaps most important in developing countries, where information sources are largely informal, is the acquisition of information from neighbors and other farmers. The process of acquiring information in this way is often referred to as social learning where a small number of leaders adopt, and the rest observe before taking action[1].

Relying mostly on micro-level data, studies consistently find both social learning and non-social learning to be significant(Bikhchandani, Hirshleifer, and Welch 1992; Foster and Rosenzweig 1995; Abdulai and Huffman 2005; Bandiera and Rasul 2006). (Foster and Rosenzweig 1995) study the adoption of high yielding seed varieties (HYVs) in India and identify imperfect knowledge about the management of new seeds as a key barrier to adoption. Farmers learning from either their own experience or by observing neighbors can both increase the likelihood of adoption. Similarly, Abdulai and Huffman (2005) examine farmers' adoption of crossbreeding technology in Tanzania and find that adoption depends positively on the proximity of a farm to others, without an explicit focus on social learning. On the other hand, Bandiera and Rasul (2006) consider the effect of a farmers' network of family and friends in the adoption of sunflower varieties in Northern Mozambique and find that there is a quadratic relationship between positive information externalities and the number of adopters in the network. By assuming social network effects are only identified by temporal variation in the number of adopters in the network, however, they ignore the critical observation that social learning works through interactions within each network. Such interactions mean that social learning is inherently spatial.

In this study, we examine how spatial interaction influences the adoption of new maize varieties in Mozambique. Although adopters are distributed throughout all regions and provinces of the country, adopters and non-adopters appear to cluster geographically (Figure 1). This pattern raises questions as to the nature of the relationships among farmers that may either aid adoption, in the case of adopting clusters, or hinder adoption where non-adoption appears to be the norm.

[Figure 1 in here]

We explain this pattern as a manifestation of a spatial multiplier effect generated by social learning among spatially-related farmers. In spatial models of network relationships, multipliers arise when the likelihood of one farmer adopting a new variety is driven by whether his or her neighbors have adopted. Social learning implies that adoption patterns reveal a spatial lag effect when all other potential factors leading to adoption are taken into account. We expect to observe a positive lag effect when a farmer follows their neighbors, and a negative lag effect when he does the opposite. Estimates of a spatial econometric model of adoption yield a spatial lag parameter, which we use to infer the importance of learning in well-defined social-spatial networks.

We contribute to the literature on the adoption of new agricultural technologies in three ways. We show that there exists a positive learning relationship among farmers as adoption is driven by information gained from nearby neighbors. Understanding how information-diffusion affects adoption will aid development agencies in leveraging their relationships with influential farmers in speeding the rate of new variety adoption. Second, despite clustering in the data, we find that distance is not necessarily the most important consideration. Instead, our findings show that neighborhoods are people-based rather than distance-based. This finding provides evidence counter to the popular notion that adoption in developing countries is hindered by poor infrastructure. Third, we demonstrate the importance of spatial econometrics in social environments as a policy tool in agricultural adoption.

The article is organized as follows. In the next section, we provide some background on maize production, and variety adoption, in Mozambique. In the third section, we describe the farm-level maize adoption data from Mozambique, and derive some stylized facts that the data suggest. We outline our econometric model next, and explain how a spatial probit model is both appropriate for this problem, and underutilized for studying social learning problems more generally. We present the estimation results, and discuss how they relate to both the underlying theory, and potential policy solutions to the under-adoption problem. The final section concludes, and offers some broader implications for how social learning can be expected to work beyond our specific empirical example.

Background on Maize Production and Variety Adoption in Mozambique

The agricultural sector in Mozambique provided employment to 81% of the population in 2014, and added $4.08 billion to GDP in 2012(NationMaster 2015). Agricultural production, however, is not evenly distributed throughout the country as geographical and historical factors between the regions create substantial differences in maize production, and trade. In general, Mozambique consists of two regions: The southern region specializes in providing labor to the mining industry in South Africa, while Central and Northern regions (often considered one region for economic purposes) are more agricultural in nature. Maize production is mainly concentrated in the North-Central region(Dias 2013).

Among staple foods in Mozambique, maize is the second most important, after cassava. The majority of maize production (over 80 percent) is consumed as food, with a remaining small percentage used for feed, seed or industrial materials (Dias 2013). Maize is generally sold directly to consumers in local markets, but most of the production is sold to middlemen and small traders, who sell it on to larger wholesalers in the cities at a higher price. As a general rule, prices in Mozambique are determined by market. This makes imported inputs (such as fertilizer) unaffordable for smallholder farmers - discouraging them from using inputs that can improve their productivity. Moreover, high transportation and transaction costs due to poor rural infrastructure constitute a significant barrier for rural farmers who would prefer to sell their surplus on urban markets (Arndt, Jones, and Tarp 2010).

Given the importance of agriculture to the macroeconomy, general economic growth and poverty alleviation in Mozambique are practically impossible to achieve without sustainable development of the agricultural sector. For this reason, improved varieties (e.g., improved maize and beans) have the potential to increase production, as well as increase income and improve the standard of living for farm households. Unfortunately, the rate of new maize variety adoption in Mozambique remains low – approximately 11% of agricultural households planted improved maize varieties in 2011, largely because households question the economic profitability of cultivating improved varieties of maize and other staple food crops.

In order to encourage households to adopt new crop varieties, both government and non-governmental organizations (NGOs) have increased the number of extension agents and programs since 2004 (Lopes 2010). However, only 15% of rural households had access to extension services from either the government or NGOs(Lopes 2010). This suggests that the number of households who are aware of new agricultural technologies and improved crop varieties is limited. As a result, local networks assume a critical role in facilitating the adoption of improved new varieties. Just how important local networks are, however, is an empirical question.

Data Description and Observations

Our data consists of farm-level information gathered through an annual survey administered by the Ministry of Agriculture (MINAG). Through this survey, the Mozambique government samples crop planting at a household level. The resulting dataset includes household-level observations on sociodemographic information, and descriptions of farmers familial and friend networks, in addition to a comprehensive set of production data. The National Agriculture Survey (or TIA), which was first conducted in 1993 by MINAG staff from the Directorate of Economics in collaboration with colleagues from Michigan State University, employs standards from the National Statistics Institute.

We used data from the 2008-2011 Partial Panel Survey (PP2011), which is a partial survey of TIA 2007 and TIA 2011[2]. The TIAs uses a stratified, clustered sample design that is representative of rural small- and medium-holders at the provincial and national levels[3]. Our sample includes households interviewed in 2011 and a subset of households that were initially interviewed in 2007 and re-interviewed in 2011. The survey was conducted in the provinces of Nampula, Zambia, Tete, Manica, and Sofala and includes data from 1,454 households. Table 1 shows number of households sampled in each province.

[Insert Table 1 here]

Our survey data includes several measures that serve as important controls in estimating the effect of social learning. We obtain information on household characteristics (household identification, and number of household members), access to services, associations, credits, and disasters effects, income indicators (salaried employment, self-employment, and remittances and pension), production and sales of grains, and food security and household vulnerability. For our purposes, we are primarily interested in the geographic location of each household. A pair of latitude and longitude coordinates was recorded for each household, which makes it possible to map out all respondents, and measure the distance between each pair by either Euclidean distance or nearest neighbor. Table 2 presents the variables used in our empirical model.

[Table 2 here]

In this sample, 66.6% of the household heads are males at an average of 44.35 years old with 2.98 years of education. Only 1.9% of them have had training about the new variety and only 27.9% of the sampled household heads have a paid job. A large proportion (65.5%) of the households have prior experiences with the new variety . Adopters use either self-owned seeds (29.4%) or bought seeds (20.2%). Of the households that used improved seeds, 29% sell their harvest and 48% use their harvest for own consumption. Access to extension services is limited as only 15% of the households have received information from an extension service in the past 12 months. Price information comes from NGOs (35.4%), radio (22.5%), extension (4.6%), and associations (4.5%). A small percentage (7.8%) of the sampled households are part of agricultural associations and 3.9% received agricultural credits from the government. Survey respondents reported three types of calamities that may have adversely affected maize production: drought, flood and cyclones, of which drought is the number one risk (34.4%), followed by cyclones (15%) and flood (6.7%). Given the large number of potential reasons why adoption remains low, it is necessary to specify a formal econometric model to determine the independent effect of social learning.

Econometric Model of Variety Adoption

Our econometric model a reduced-form representation of the incentives farmers face to adopt new maize varieties. As a reduced-form model, we do not explicitly describe the relative profit from new varieties, but factors that influence profitability. Our primary hypothesis is that social learning is the primary way in which farmers learn new ways to grow maize more profitably.

Our model is based on the assumption that social interactions, and hence social learning, are best modeled as spatial phenomenon. The analogy between social relationships and space is not a new one, as Yang and Allenby (2003), Narayan, Rao, and Saunders (2011), and Richards, Hamilton, and Allender (2014) consider explicitly spatial econometric models of social interaction. In this case, a spatial latent variable model is a formal representation of the equilibrium outcome of social and spatial interaction. Even though the actual dynamics of the interaction among agents (peer effects, neighborhood effects, spatial externalities) cannot be observed due to the single dimension of observations for a single point in time, the correlation structure that results from the equilibrium can be captured in a relatively simple spatial model(Brock and Durlauf 2001; Durlauf 2004).

Consider the underlying incentive for a farmer to adopt as an unobserved, or latent, construct of utility defined as y_i^*. Adoption, written as a binary variable $y_i^*$is only observed whenever $y_i^* > c$ for some threshold value, c When the latent incentive to adopt is affected by the decisions of others, the resulting spatial lag model is written as Anselin (2002):

(1) $\quad \mathrm{y}_i^* = \rho \sum_{j \neq \text{ß}}^{n} w_{ij} y_i^* + x_i' \beta + u_i,$

where y_i^* is a $n \times 1$ vector of unobserved utility measures, and and are elements of their respective matrices.

Let the threshold $c = 0$, and let y_i be the binary outcome whether a farmer will adopt or not, taking on the value of 1 (adopt) whenever utility $y_i^* > 0$. The threshold value is set to zero indicating that when the utility of adopting the variety is positive we observe the action of adoption. The probability of adoption is then:

(2) $$Prob[y_i = 1] = Prob[u_i < \rho \sum_{j \neq \text{ß}}^{n} w_{ij} y_i^* + x_i' \beta].$$

Equation (2) describes the adoption decision made by each farmer, which is in turn a function of the decisions made by all other farmers. Therefore, we represent the decisions taken by all farmers in the sample in matrix notation as:

(3) $$\boldsymbol{Y} = (1 - \rho \boldsymbol{W})^{-1} \boldsymbol{X} \beta + (1 - \rho \boldsymbol{W})^{-1} \boldsymbol{X} u,$$

where $\boldsymbol{Y}$ is a vector of binary adoption decisions, $\boldsymbol{X}$ denotes a $n \times k$ matrix of factors that may influence adoption decisions, $\boldsymbol{W}$ is the weight matrix that indicates the spatial relations among farmers, and u is an idiosyncratic shock.

Clearly, the spatial weight matrix plays an important role in the spatial autoregressive model. We compare estimates from three alternative weight matrices. First, we use a weight matrix based on rook continuity in which only observations that are adjacent to the focal observation in rook fashion are considered neighbors.[4] The advantage of a contiguity matrix is that it emphasizes immediate neighbors, who are the most accessible information sources. Intuitively, direct neighbors should have an outsize influence on adoption decisions because acquiring information is a costly process. If farmers implicitly weight the marginal benefit of additional information against the marginal cost of doing so, nearest neighbors will be the lowest-cost source of information.

Second, we use a distance-based weight matrix, where the relative distance between observations measures the strength of spatial relationship between two farmers. Our distance metric is arc-distance, which addresses not only the direct natural distance between observations, but also slopes (or valleys) that represent important barriers to communication that are not captured by simple "as the crow flies," or Euclidean distance. The advantage of a distance-based matrix is that it represents the true travel distance between households. One important disadvantage, however, is the questionable relevance of physical distance when communication by electronic means is as likely as direct observation or talking.

Our third matrix is based on the concept of a "nearest-neighbor". A nearest-neighbor matrix is one in which proximal farmers are coded as 1, and all others 0, to indicate that only farmers that are most near are likely to exert any sort of spatial influence. An advantage of a nearest-neighbor weight is that, unlike continuous weights, a nearest neighbor matrix pertains to only immediate neighbors, which permits relationships among households that transcend geographical limitations. For example, proximity can be defined in terms of socio-economic background rather than geographic distance.[5] A disadvantage of this approach, however, is that discrete measures assign importance only to one farm, while the true effect could be a function of the influence from many other farmers.

We include five categories of explanatory variables in the $\boldsymbol{X}$ matrix, namely farm identification variables that includes a set of provincial fixed-effects, household characteristics variables that describe the socio-demographic profile of each farm-household, production and sales variables that measure each farm's production history, non-social learning that describes the sources of information besides social learning, and a set of risk variables that describe sources of profit-uncertainty facing Mozambique farmers. The selected variables are presented in Table 2.

[Insert Table 2 here]

Among household identification variables, we expect the Central regions to show a higher adoption rate as maize is more commonly grown the Central regions. Socioeconomic attributes are variables that measure observed heterogeneity, and in that regard are likely to explain some of the observed variation in adoption rates. Within the set of socioeconomic attributes available in the TIA data, we expect education to be positively related to adoption because educated people are presumably better able to process information, and possess a better understanding of the market. If new varieties are indeed better, then higher education should correlate with adoption. Age of the household head has an indeterminate effect on adoption. While experience can play a very important role in that more experienced individuals may have more accurate prior about the new variety, making them more likely to adopt, older farmers can be set in their ways and less likely to switch to a new variety.

Other potentially-important variables include the availability of government information sources. We expect that receiving agricultural credits and being a member of an agricultural association have positive effects on one's adoption decision. Credits are given to farmers as an incentive to produce certain crops, and as a way to alleviate the damage caused by any natural disasters. Being a member of an association not only provides the opportunity to learn about new varieties, but also exposure to market information and advances in production methods.

Other farm-related attributes may also explain some inter-farm variation in new variety adoption. First, we included variables that describe whether a farmer's harvest is intended for own-consumption or for sale. Smaller size farms tend to produce for their own consumption where as bigger farms supply some proportions of their harvest to local factories. Therefore whether a farm's harvest is intended for own consumption and selling is a good indicator of the operation of the farm. Natural disasters may also slow adoption. In order to capture the influence of such, we included the occurrences of drought, flood and cyclone specific to that farmer's region in the past 12 months. In Mozambique, wildlife poses the most important risk, so we capture this effect by including a variable to indicate whether the crops were attacked by wildlife in the past 12 months.

In the next section we discuss issues that arise in estimating spatial probit models, specifically in the context of Maize adoption. Spatial econometric models are powerful in that they are able to encapsulate a large amount of information in a relatively simple form, but at the cost of estimation complexity. In our case, including the neighbors' adoption decision in a regression model induces endogeneity because the choices made by everyone else in the network are correlated with unobservable factors, by definition. We discuss the complications caused by correlated observations and the methods we use to tackle them.

Estimation and Identification

There are two types of spatial dependences: Lag dependence, which studies the influence between an individual (or unit) and his (its) neighbors, or error dependence, which focuses on how unobserved factors are spatially-related. In our case, learning is an example of lag dependence because information is transmitted among farmers, and its effect is expected to decay as social distance grows. A spatial lag model can capture the nature of such decay, or in other words, how is information reserved among neighbors. Therefore, prior to estimating with an explicitly spatial routine, we follow Pinkse and Slade (1998) by testing for spatial dependence in a discrete-choice environment. The Pinkse−Slade LM test statistic is:

$$(4) \quad LM_{ps} = \frac{(\varepsilon_i\prime W\varepsilon_i)^2}{tr(WW+W'W)'},$$

where $\varepsilon_i = \frac{y_i-\Phi_i}{\sqrt{\Phi_i(1-\Phi_i)}}$, and Φ_i is a n-dimensional multivariate normal cumulative distribution function. In Pinkse and Slade (1998), the residuals are standardized generalized residuals, so as to correct for the inherent heteroskedasticity in the model. The asymptotic distribution is not formally derived but, instead, a bootstrap procedure is suggested for carrying out inference[6]. Because we reject the null of a traditional probit (p=0.0135), we estimate a spatial probit (or a spatial latent model by Anselin (2013)).

Our dependent variable, adoption, is inherently discrete as discussed in (2). Estimating the non-spatial (classic) probit model consists of a straightforward application of the maximum likelihood principle with the log likelihood function as:

$$(5) \quad lnL = \sum_i^n [y_i ln\phi(x_i'\beta) + (1-y_i)ln(1-\phi(x_i'\beta)],$$

where y_i is an independent draw from a binomial random variable with probability $\phi(x_i'\beta)$. For the spatial probit model with lag specification, the log likelihood function becomes:

$$(6) \quad lnL = ln\Phi_n[\{\boldsymbol{Q}(1-\rho\boldsymbol{W})^{-1}\boldsymbol{X}\beta;0,\Sigma_\rho],$$

where $\boldsymbol{Q}$ is a diagonal matrix with diagonal elements $q_i = 2y_{i-1}$, and Φ_n is a n-dimensional multivariate normal cumulative distribution function with the upper bound as $\boldsymbol{Q}(1-\rho\boldsymbol{W})^{-1}\boldsymbol{X}\beta$, mean 0, and variance-covariance matrix Σ_ρ.

The evaluation of (5) involves the computation of n-dimensional integrals, which is unpractical(Anselin 2013). Beron and Vijverberg (2004) outline a simulation estimator for the spatial probit model based on the relative importance sampler (RIS) for an n-dimensional multivariate normal density. This method involves an estimate for the log-likelihood as the average of the sampled joint probabilities:

$$(7) \qquad \hat{p} = (1/R)\sum_{r=1}^{R}[\prod_{j=1}^{n}\Phi(\bar{v}_j, r)],$$

where V is $Q(1-\rho\boldsymbol{W})^{-1}\boldsymbol{X}\beta$, and Σ_ρ proxies based on the Choleski tansformation.[7] We adopt this approach in estimating the spatial probit model in our variety-adoption data.

Results and Discussion

We first present a set of specification tests in order to establish the validity of our spatial model. To test for spatial lag dependence, we employ a Lagrange Multiplier (LM) test statistic for the spatial autoregressive process (Anselin 1988). We considered a number of alternative models, including a non-spatial probit model, a spatial model using arc distance weight (Model 1), a spatial model with rook contiguity (Model 2), and a model using nearest-neighbor weights (Model 3).

The null hypothesis is that there exists no spatial dependency among neighbors in Mozambique. Comparing the LM [8]Lag test value against the critical value suggests that the null is rejected, meaning that Mozambique farmers based their decisions of adoption on other people. More specifically, they base their adoption on immediate neighbors and extended neighbors, but not on people who live in closest arc distance[9]. Table 3 shows the results from comparing each specification against the non-spatial null model. A spatial model is indeed preferred in explaining the sample adoption data using nearest neighbors ($LM = 5.956 > \chi^2_1$) and rook neighbors ($15.766 > \chi^2_1$) as proximity among households[10]. However, distance does not explain the adoption decision among households as the Chi-square LM value is smaller than the critical Chi-square value.

The value of the spatial lag parameter represents the nature of spatial influence, conditional on a particular weight definition. In this case, spatial lag parameters for both the rook contiguity and nearest neighbor definitions are statically significant. Table 4 shows the estimation results from each spatial model, using arc-distance, rook contiguity, and nearest neighbor definitions. In each case, the magnitude of spatial dependency is represented by the value of ρ, with nearest neighbor having a lower dependency (0.0625) and rook contiguity having a higher dependency (0.5086). A positive spatial lag ρ indicates that neighbors have a positive effect on the focal famer with regards to maize adoption where as a negative spatial lag indicates that the focal farmer tends to employ the opposite strategy as his neighbors. The value of ρ illustrates the magnitude to which the farmer's neighborhood influences his adoption, with a higher ρ indicating a higher dependency and a lower ρ indicating a low dependency. From the results shown in table 4, we conclude that a farmer has a high dependency on his nearest four neighbors (rook contiguity) and a low dependency on his one nearest neighbor. This finding combined with the geographic allocation[11] of farmers further implies that information among Mozambique farmers transit in a more collective network. Moreover, we notice that defining the spatial weight matrix based on arc-distance does not generate a significant spatial lag parameter. This shows that even though neighbors are likely to live in close proximity, distance does not confine information exchange. In other words, the neighborhood that influence maize adoption is not constructed on distance.

In term of goodness-of-fit, we use two criterions: the Alkaike Inofmration Criterion (AIC)(Akaike 1974) and the pseudo R^2 (Lesage 1998). Model 2 possesses the lowest AIC of the three. Because lower values of AIC are preferred, this measure of fit supports the rook contiguity specifications as the preferred model. Lesage (1998) derives an expression for the coefficient of determination (R) for a spatial model that is analogous to the R^2 for OLS, but includes the spatial weight specification, so is referred to as a pseudo R-squared[12]. According to the pseudo R^2 statistic, the rook contiguity model has the highest value (8.93%) than either of the other two models. Therefore we choose Model 2 as our preferred model for parameter interpretation.

[Insert Table 3 here]

Theories of social learning imply that there is a spillover effect when the learning effect is significant (Bandiera and Rasul 2006). Our findings support the existence of spatial spillovers in learning as there is a strong spatial dependency among neighbors, regardless of immediate neighbors or extended members. Essentially, famers are inter-connected and learn by observing each other′s adoption decision. We assume simultaneous influences of the famer on his neighborhood and vice verse, and discover a positively relationship between the two. When the neighborhood is pro-adoption, the farmer is more likely to adopt the new maize variety. When the neighbor is anti-adoption, the farmer is more likely to stay with the traditional variety. Therefore, having more adopters will encourage farmers to adopt while having more non-adopters will prevent farmers from adopting. This finding explains the clusters that are presented in Figure 1, where adopters tend to reside in close proximity, separate from non-adopters.

Moreover, our results show that such clusters are not caused by regional differences, as none of the province fixed-effects are found to be significant. From this, we conclude it is neighbors that play an important role in new maize variety adoption in Mozambique rather than regional differences. These findings suggest one immediate implication for policy. Namely, to promote new varieties, government agencies charged with promoting the adoption of new varieties could leverage influential farmers within each region, ensuring that they adopt, and others are aware of their adoption. Once farmers receive positive feedback from the new varieties, they will share their experience among others in their network, and our results suggest that other farmers will follow.

[Insert Table 4 here]

Non-social learning also plays an import role in explaining variation in adoption rates. Education, training and extension are all found to be significant and positively related to adoption. More specifically, one year of education increases the adoption probability by 0.9%, having access to extension services increases the probability of adoption by 6%, and perhaps more importantly, having specific training about the new variety increases the probability of adoption by 20%. Clearly, famers prefer direct, hands-on help with planting new varieties. From a policy standpoint, agencies interested in promoting adoption should focus on retaining existing adopters as well as recruiting new adopters by perhaps offering follow-up technical training or feedback on the desirability of new varieties. Credit is found to be another factor that promotes adoption, meaning that government subsidies are crucial in convincing farmers to switch from a familiar variety to a new one. Existing subsidies/credits in Mozambique include a discounted electricity program, input-discount packages, and low-interest loans for small famers(Dias 2013). These are essential incentives and should be continued.

Moreover, we find that the intended use of the crop is an important predictor of adoption. Specifically, if a farmer produces for sale instead of own consumption, he is more likely to apply the improved variety. In Mozambique, small farms face the obstacle of transporting their surplus to the deficit area in the south, so they can only operate in small scale. On the other hand, larger farmers possess economies of scale, and better able to absolve transportation cost in order to sell their surplus. Therefore, although the new variety has the advantage of improving yield, an attractive trait to both small farms and larger farms, only the larger farms are able to take advantage of the trait. This calls for unified organizations or clubs that take care of the supply chain for small farm surplus. For example, if there is exits community clubs that charge a small membership fee to arrange for transportation of its members′ harvest to the southern provinces, more small holders will be motivated to employ the high-yield variety.

Conclusion

In this article, we investigate social learning in the context of maize adoption in Mozambique. We find that a farmer's neighborhood provide a positive learning effect in the sense that farmers who learn from other farmers are more likely to adopt a new maize variety. Given the informational barriers facing farmers who are considering new variety adoption, we interpret our findings as revealing a central role for farmer-to-farmer communication of knowledge regarding new varieties. That is, connections with other farmers provide positive information externalities, which in turn encourage adoption.

We examine maize adoption data from Mozambique using an explicitly spatial econometric model. We assume a farmer observes his neighbors and that such a learning process is disseminated through neighborhood defined by various weight matrices. Others have investigated the role of neighborhood influences on innovation diffusion, but they do not treat neighbor interactions as simultaneous. By employing a spatial lag model, we address the simultaneous relationship between a farmer and his neighboring farmers by specifying social weight matrices that are able to parameterize a large number of alternative neighbor-relationships. We find significant spatial effects when social space is defined by nearest neighbors and extended neighbors. Such positive effects indicate that Mozambique farmers copy their neighbors' decisions, hence forming spatial clusters of adopters and non-adopters.

Throughout, we focus the discussion around social learning as the underlying mechanism connecting decisions within a network. Social learning is important in this context because a lack of information is a key barrier to adoption in our setting. Our primary finding is that local networks act as important agents for information exchange. Farmers rely on their immediate neighbors for recommendations, and weigh the neighbors' opinions heavily. Farmers also go beyond immediate neighbors to exploit extended social networks for gathering information. Moreover, although existing research attributes low Maize production to underdeveloped infrastructure and transportation cost, we show that social learning is not constrained by distance. That is, the dissemination of knowledge on new variety transcends distance to extended neighbors. Hence, unlike the regional differences in Maize production, there are no regional differences in new variety adoption.

Besides social learning, we find non-social learning to be important in adopting new variety as well. Direct training such as extension plays an important role in persuading farmers to switch from traditional to new variety. Government subsidies and credits encourage adoption by alleviating the production cost. Larger farmers are more likely to adopt than smaller farms because of a more robust supply chain. Since small farms have to bear higher transportation cost, Mozambique government should build an efficient demand-supply market for small holders in order to encourage economies of scale.

A natural implication of our research is that, in order to promote new variety, the Mozambique government should focus on community development. That is, to strengthen connections among members of local networks, to develop local thought-leaders, and to provide information directly to neighborhood communication channels Once a farmer adopts, the network will create a ripple effect that recruits more adopters.

This study only investigates new varieties of maize, which is one of the staple food in Mozambique. Given data availability, similar research can be carried out to study other crops, and in other developing-country contexts. We also ignore regional differences as we find them to insignificant in explaining neighborhood effect in our case. However, due to the segregation of the economy and culture between the Southern part of Mozambique and the Northern and Central parts of Mozambique, it might worth one′s time to investigate the adoption within these regions.

Notes

[1]To make a clear distinction between social learning and the other sources of information, we define information acquired from sources such as education, social media, extension service and organizations as non-social learning. Non-social learning differs in that it is typically constrained by the availability of resources, from learning materials, to income, and lack of government support.

[2]We thank the Michigan State University for the data they provided. Information on availability and access to the Data are available at: http://fsg.afre.msu.edu/Mozambique/survey/index.htm.

[3]Smallholders are the backbone of the agricultural sector. A smallholder is defined as having less than 10 hectares of cultivated area, fewer than 10 cattle, 50 goats, pigs or sheep, and 5,000 chickens (TIA Dissemination, 2007). It is estimated that there are over 3 million such smallholders in the country. Smallholders practice rain-fed agriculture, operate at low levels of productivity. Most smallholder production is committed to own-consumption, but there has been considerable growth in the marketing of both basic food crops and cash crops by smallholders.

[4]Similar to chess terms, rook continuity refers to two polygons sharing common boundaries.

[5]For example, the nearest neighbors of a focal farmer can be from the same geographic region, or they can be across regions, but possess some underlying economic similarities such as accepting loans from the same bank. For example, if accepting credits/loans is a crucial for farmers' adoption decisions, farmers should express similar behavior based on the mutual loan policy.

[6]See Pinkse and Slade (1998) ,p. 131.

[7]Please find computational details in Beron and Vijverberg (2004), pp. 176.

[8]Intuitively, the LM tests the residuals from a non-spatial probit model against a series of spatial models that differ only in their weight specifications.

[9]We test the null against three neighbor specifications: immediate neighbors, extended neighbors, and neighbors based on arc distance. We rejected the null with the first two specifications but not with the last one.

[10]Note that the spatial lag parameters are significant for contiguity (p = 0.0001) and nearest neighbor (p = 0.0016), but not for arc-distance (p = 0.5389).

[11]that many small-holders live densely in a village.

[12]The pseudo R^2 like a traditional R^2, measures the portion of variation in data explained by the spatial model relative to the amount of total variation, and provides a measure of goodness fit.

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Figures

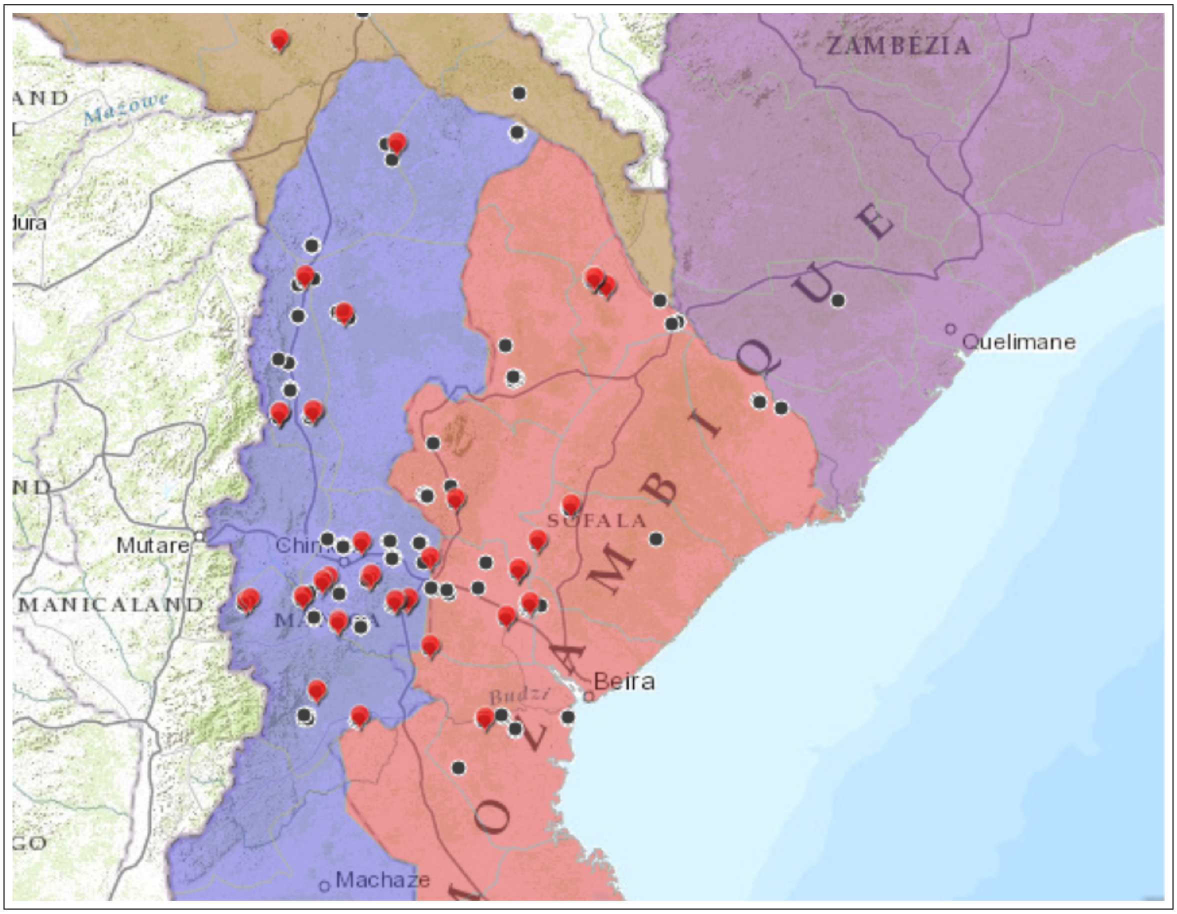

Figure 1. Sampled Household in Sofala and Manica with Adopters (red) and Non-adopters (black).

Tables

Table 1. The number of adopters in the sampled provinces

	Nampula	Zambezia	Tete	Manica	Sofala
Number	263	330	277	244	340
Percentage	18.1%	22.7%	19.1%	16.8%	23.4%

Table 2. Selected Variables and Descriptive Statistics.

Variables	Definition	Descriptive Statistics	Frequency
Farm Identification			
Nampula	The households belong to Nampula province		
Zambezia	The households belong to Zambezia province		
Tete	The households belong to Tete province		
Sofala	The households belong to Sofala province		
Household Characteristics			
HH_Gender	Gender of the household	1= male	66. 6%
		0= female	14.60%
HH_Age	Age of the household head	44.35(13.856)	
HH_Education	Years of education for the household head	2.98(2.993)	
HH_Training	The household had agricultural training in the past 3 months	1= yes	1.90%
		0 = no	79.30%
HH_Job	The household head had salaried employment	1= yes	27.90%
		0 = no	53.20%
Production and Sales			
Improve	Grew improved maize variety in 2011	1=yes	11.30%
		0= no	65.60%
ImprSeed_Own	Owned improved maize seeds	1= yes	29.40%
		0= no	47.50%
ImprSeed_Buy	Bought improved maize seeds	1=yes	20.20%
		0=no	56.70%
Impr_Sell	Sold the maize grown with improved seeds	1=yes	29%
		0=no	48%
Non-social learning			
Info_Extension	Received information or advice from extension in the past 12 months	1=yes	15%
		0=no	66.20%
InfoPrice_Radio	Price information from radio	1=yes	22.50%
		0=no	58.70%
InfoPrice_Extension	Price information from extension	1=yes	4.60%
		0=no	76.50%
InfoPrice_NGO	Price information from non-government organizations	1=yes	35.40%
		0=no	45.70%
InfoPrice_Assc	Price information from agricultural association	1=yes	4.50%
		0=no	76.70%
Mem_Assc	Member of agricultural association	1=yes	7.80%
		0=no	73.40%
Credit	Received agricultural credits.	1=yes	3.90%
		0=no	77.20%
Training	Received training in the past 3 months	1= yes	2.20%
		0= no	97.80%
Risk Factors			
Risk_Flood	Lost crops due to flood in the past 12 months.	1=yes	6.70%
		0=no	74.40%
Risk_Drought	Lost crops due to drought in the past 12 months.	1=yes	34.40%
		0=no	47%
Risk_Cyclone	Lost crops due to cyclone in the past 12 months	1=yes	15.60%

Table 3. Diagnostics for spatial dependence test against a classic Probit

Test	Arc Distance(Model1)	Rook Contiguity(Model 2)	Nearest Neighbors(Model 3)
LM Lag	0.377	15.766*	5.956*
Log-likelihood	-288.397	-282.005	-285.813
AIC	602.782	590.011	597.627
Pseudo R2	7.34%	8.93%	8.47%

Note: an asterisk indicates significance at 0.05.

Table 4. Spatial models using different weights.

Variable	Arc-distance	Contiguity (rook)	Nearest Neighbor
Constant	0.0211	0.0211	0.0910
	(0.1399)	(0.6222)	(0.027)
Education	0.0097*	0.0075	0.0009*
	(0.0038)	(0.0556)	(0.0038)
Training	0.3551*	0.3572*	0.3562*
	(0.0778)	(0.0000)	(0.0773)
Extension	0.0682*	0.0710*	0.0699*
	(0.0299)	(0.0175)	(0.0298)
Nampula	-0.1142*	-0.047	-0.1053*
	(-0.0417)	(-0.2882)	(-0.0342)
Tete	0.0001	0.0074	0.001
	(0.0304)	(0.8057)	(0.0302)
Zambezia	-0.0314	-0.0102	-0.0305
	(-0.0307)	(-0.7503)	(-0.0303)
Association	0.0162	0.0084	0.0168
	(0.0387)	(0.8267)	(0.0385)
Credit	0.1102*	0.1360*	0.1140*
	(0.0561)	(0.0168)	(0.0558)
Risk_flood	0.0383*	0.0331	0.0422*
	(0.0436)	(0.4456)	(0.0433)
Sale	0.0432*	0.0389	0.0440*
	(0.0236)	(0.0971)	(0.0233)
ρ	0.5685	0. 5086*	0.0625*
	(0.9709)	(0.0163)	(0.0257)
Lagrange Multiplier	0.3774	15.7662*	5.9562*
Prob. of LM (H0:$\rho = 0$)	0.5389	0.0001	0.0014
Log-likelihood	-288.397	-282.005	-285.813
Pseudo R^2	7.34%	8.93%	8.47%

Note: an asterisk indicates significance at 0.05. Standard errors are in parentheses.