Received: 20 April 2020 | Revised: 18 February 2022 | Accepted: 22 March 2022

DOI: 10.1111/agec.12722

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists
IAAE
WILEY

ORIGINAL ARTICLE

Social interaction and geographic diffusion of iron-biofortified beans in Rwanda

Jose Funes[1,2] | **Laixiang Sun**[2,3] | **Fernando Sedano**[2] | **Giovanni Baiocchi**[2] | **Todd Benson**[4]

[1]District of Columbia - Office of Planning, Washington, District of Columbia, USA

[2]Department of Geographical Sciences, University of Maryland, College Park, Maryland, USA

[3]School of Finance & Management, SOAS University of London, London, UK

[4]Independent International Food Policy Researcher, Washington, District of Columbia, USA

Correspondence
Jose Funes, District of Columbia Office of Planning, Citywide Strategy and Analysis: Data Analysis and Visualization Unit, Washington DC, 20024, USA.
Email: jefunes@terpmail.umd.edu

Abstract

This study analyzes smallholder farmers' decisions to adopt beans with higher levels of dietary iron developed through a conventional breeding technique called biofortification. We approach this study by applying spatial econometric techniques to estimate neighborhood influence and to determine the factors driving the adoption of iron-biofortified beans (IBB). We employ a cross-sectional, nationally representative survey of bean producing households from 2015 bean growing season B in Rwanda, and present results for growers of both bush and climbing varieties of beans. The results show geographic diffusion of iron bean planting material occurs among neighboring farmers that exhibit interdependent decision-making patterns, as well as similar characteristics relative to the group. Some policy implications can be drawn from the results. First, a differentiated geographical targeting strategy for bush and climbing bean varieties as a function of farmer and farm characteristics should increase iron bean adoption rates. Second, strengthening partnerships with delivery agents and extensionists should stimulate the adoption of IBB varieties. And finally, technology-promotion programs that consider progressive farmers and strengthen social interactions and group activities among peer networks should increase the spread of information and diffusion of IBB.

KEYWORDS

iron-biofortified beans, neighborhood effect, Rwanda, social interaction, spatial diffusion, spillovers

JEL CLASSIFICATION

C12, C31, D01, O14, R23, Q12, Q18

This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.
© 2022 The Authors. *Agricultural Economics* published by Wiley Periodicals LLC on behalf of International Association of Agricultural Economists.

1 INTRODUCTION

Common bean (*Phaseolus vulgaris*) is the most important legume and one of the most vital sources of protein for Rwandan families (Petry et al., 2015). Beans are staple food crops in Rwanda and as such, the country ranks number 1 out of 81 countries suitable for investing in iron-biofortified beans (IBB) (Asare-Marfo et al., 2013). At the same time, Rwandans have one of the highest per capita bean consumption rates in the world, with rural households consuming significant quantities of beans on average of 6 days in a week (Asare-Marfo et al., 2016; Berti et al., 2012; Food and Agriculture Organization of the United Nations [FAO], 2020). In 2010, the National Agricultural Research System of Rwanda, namely the Rwanda Agriculture Board (RAB), in collaboration with the International Center for Tropical Agriculture (CIAT) and HarvestPlus, officially released the first IBB varieties for planting by farmers in Rwanda. On the supply or product side, these biofortified varieties not only had higher micronutrient density, but also demonstrated better yield performance and resilience to growth-reducing factors, like pests and diseases, and growth-limiting factors, such as droughts. However, at the time of their release, little was known about the demand side, such as the key farm and farmer level factors that would affect their adoption and, in particular, the role of peer influence thereon. Understanding the factors that drive IBB adoption among bean farmers is critical to inform the design of policies and programs that increase not only the production and consumption of IBB varieties, but also of other improved agricultural technologies in Rwanda.

IBB is a relatively new technology. Farmers may be risk-averse when they lack information pertaining to the likelihood of occurrence of the possible outcomes (e.g., yield, costs, profitability) of the new technology and such risk-averse attitude would exert a detrimental impact on adoption. Farmers may be uncertain about the economic returns of the new technology owing to insufficient knowledge about the types and costs of inputs needed, the yield distribution, expected market prices, and the demand for the produce (Ghadim & Pannell, 1999; Tessema et al., 2016). In this context, social learning and social networks often complement and/or act as substitutes in delivering information and facilitating the technology diffusion process.

In his seminal work, Manski (1993) identified three sources of social influence in the adoption of a technology: (1) endogenous effects; (2) exogenous network effects; and (3) correlated effects. The endogenous effect emphasizes that the adoption behavior of individual farmers would be influenced by their neighbors' adoption outcomes, as a result of peer learning about the profitability or the appropriate use of the new technology, or of merely wanting to conform with observed peer behavior. The exogenous effect highlights the contextual interactions, wherein the propensity of an IBB grower to behave is correlated with the exogenous characteristics of his/her neighbors. The correlated effects emphasize that small holder farmers in the same group tend to behave similarly because of commonly observed and unobserved characteristics of the group, for example, sharing a common institutional or physical environment (Tessema et al., 2016). All these three effects imply a spatial contextualization of the diffusion of IBB varieties, meaning that the decision of a bean growing household to adopt an iron bean variety is spatially correlated. Farmers' decisions to adopt IBB depend not only on their own farmer and farm-level characteristics, but also on the decisions of neighboring bean farmers and their personal and farm level characteristics.

Communicating the benefits of growing and consuming IBB varieties is also expected to influence IBB adoption, as per the technology adoption literature (Abdulai et al., 2008; Foster & Rosenzweig, 2010). Under this spatial context, a bean growing household that is close in proximity to a household who is an IBB grower should have a higher probability of being an IBB adopter, which is the endogenous effect. Another condition relates to the social characteristics of a group as the main factor in spatial clustering, which is the likelihood of an individual to behave, on average, in agreement with their social group. Whether or not the diffusion of IBB varieties is geographically driven, the spillover effects will lead to a strong spatial relationship, that is, farmers with similar IBB adaptation behavior being in the same geographical area. Each one of these sources of social influence would have different policy implications.

Indeed, literature on the significance of social interactions in the realm of capacity development is wide-ranging and well-established (see e.g., Durlauf & Ioannides, 2010). Interest in the role of social learning in promoting agricultural technology diffusion has grown in recent years. Here we highlight recent salient empirical work on this topic. Conley and Udry (2010) used individual-level data of pineapple farmers in Ghana to provide an empirical analysis to measure the importance of social learning. Their results support the notion that farmers are learning from neighboring farmers' experience and that novice farmers are likely to adopt new technologies faster than experienced farmers. Foster and Rosenzweig (2010) provided a review of studies focused on the adoption of new technologies in low-income countries. They summarize that the key factors affecting the adoption of a new technology are financial conditions, social learning, technological externalities, scale economies, schooling, credit constraints, and incomplete insurance. Krishnan and Patnam

(2014) used data from Ethiopia to examine the effect of learning from extension agents and learning from neighbors. They found that the adoption of fertilizer and especially of better seeds is slow. Learning from adopting neighbors is mainly responsible for the spread of these technologies. Ward and Pede (2015) used a nationally representative data from Bangladesh. They found that a network of hybrid rice adopters has a higher influence than a distance network of hybrid rice adopters. They show that network effects play a more important role in hybrid cultivation than agricultural extension services. In summary, social learning theories and models conclude that social learning plays a key role in the spread of agricultural technology, and farmers' decisions to adopt a new technology are influenced by the decision and knowledge of neighboring farmers. Common spatial econometric methods applied to technology adoption include the spatial error model and the spatial lag model (Holloway et al., 2002; Ward & Pede, 2015). In this article, we expand this literature by modeling the endogenous and exogenous network effects using the spatial Durbin model (SDM) (Anselin, 1988; J. LeSage & Kelley Pace, 2009), which allows for an enhanced understanding of IBB adoption as it relates to neighboring characteristics. In addition, we employed multilevel modeling to control for correlated effects in which takes into consideration that the outcomes of smallholder farming households in the same village are impacted by the same observed and unobserved correlated effects.

What sets this article apart from the large literature on agricultural technology adoption in low and middle-income is that it combines methods and theories from economics and geography to understand the importance of interdependence and spatial spillovers on the diffusion of agricultural technology, particularly of IBB. This article further contributes to this topic by offering a social interaction model that incorporates endogenous social interaction, individual exogenous characteristics, as well as contextual effects. In addition to quantifying the extent of the endogenous and contextual effects, this article provides a detailed and comprehensive discussion of the relative magnitude of direct and indirect effects. These effects are not considered in the existing literature pertaining to the role of social interaction on the adoption of agricultural technology. This last part helps to answer the question of the significance of spatial spillovers in influencing neighboring farmers in adopting IBB. Furthermore, we use the spatial multilevel estimator to characterize the relative influence of correlated effects on the adoption of IBB. In sum, the presence of significant spillovers may help to estimate the benefits of a″ program or policy and the multilevel analysis represents an alternative way of capturing unobserved spatially correlated effects. The correlated effect is useful to characterize, map, and understand how villages might affect one another when the multilevel structure is incorporated into a spatial model.

Shaped by locality and constrained by social geographic distance, we model social interactions by setting geographic neighbors' relationships. By social interactions, we refer to interdependence among smallholder farmers in which preferences, tacit knowledge, expectations, and constraints faced by one farmer are directly influenced by the characteristics and choices of others. In this article, we are interested in the importance of tacit knowledge as it directly pertains to farming experience and know-how of the use of IBB and farm management practices in smallholder farming households. In spatial regression analysis, measures of spatial interaction include the spatial autoregressive (SAR) parameter through different spatial weight structures. The SAR parameter represents a way to model structured dependence between observations that arise from peer effects (Case, 1992; J. LeSage & Kelley Pace, 2009). The SAR parameter in technology adoption studies contains important policy information. Mapping interactions of farmers' IBB adaptation behavior can provide guidance to new technology delivery programs on how specific initial investments in technology promotion can generate further geographic diffusion (Conley & Udry, 2010; Holloway et al., 2002).

This article analyzes farmers' adoption of IBB varieties by specifically examining the influence of demand-side factors and the role of peers. We draw on several theories from studies on the adoption of agricultural technology, social behavior, and spatial econometric methods to build our models. We test for the presence of a spatial association between economic agents (farmers), estimate prevalence rates of IBB adoption by district, and examine any potential interactions with contextual factors. We implement spatial probit (SP) models for discrete-choice data using Bayesian modeling. The use of Bayesian modeling to estimate spatial processes allows estimating more realistic models (Anselin, 1988; J. LeSage & Kelley Pace, 2009). These new methods produce useful measures of direct and spatial spillover impacts from changes in the explanatory variables (Lacombe & LeSage, 2018; J. LeSage & Kelley Pace, 2009).

The remainder of this article is organized into three sections. Section 2 sets out the conceptual framework for the study and gives the general descriptive statistics for the variables used in our analysis. Section 3 analyzes the determinants of IBB adoption and spillover effects in Rwanda. Section 4 provides conclusions and policy recommendations.

2 | CONCEPTUAL FRAMWORK, DATA, SURVEY STATISTICS, AND COVARIATES

2.1 | Theoretical consideration

Our theoretical framework applied to the adoption of agricultural technology draws concepts on social interaction from Conley and Udry (2010) and Ward and Pede (2015) and concepts on optimal choice and utility maximization from Abdulai et al. (2008). We make two broad assumptions (1) a smallholder farming household's decision to grow IBB varieties is based on utility maximization theory and (2) new IBB varieties produce higher yields conditioned to the use of modern inputs and management practices. There is also an element of uncertainty because farming households are less familiar with the IBB varieties. The structure of the production function of a smallholder farming household for the period t and future period *t +1*,

$$y_{i,\, t+1} = f\left(M_{it}, k_{it}, \omega\right) + \varepsilon_{i,t+1}. \tag{1}$$

where $y_{i,\, t+1}$ is farming household's future output, M_{it} is the quantity of inputs used in the current period, k_{it} is the farming household's level of information used in the current period, - environmental conditions, and ε_{i} is an i.i.d disturbance for household *i* with zero mean and σ^2. ε_{i} is assumed to follow a normal distribution. The profit function is,

$$\prod_{i,\, t+1} = P_{t+1}\, f\left(M_{it}, k_{it}, \omega\right) - C_t$$

$$= \max\left[P_{t+1} f\left(M_{it}, k_{it}, \omega\right) - \psi M_{it} - \zeta k_{it}\right]. \tag{2}$$

$\Pi_{\mathrm{i},\, t+1}$ indicates that the value given by the function is the maximum profit that can be obtained at a given local market price. *C* is the cost of production. Only the variables M_{it} and k_{it} are under the smallholder farming household's control. The farming household chooses levels of these inputs, *M* and *k*, in order to maximize profits. The smallholder farming household maximum profits depends on these three exogenous prices, P, ψ, ζ together with the form of the production function.

The other two sets of assumptions include (1) farming households' profit expectations depend not only on their own experiences, preferences, but also on their social interaction with other farmers' experiences, expectations, and constraints, and (2) social interaction occurs in local places and its strength depends on the relative social geographic distance between IBB adopters and their neighbors. Therefore, assuming that the farmer maximizes the expected profit Π, as shown in the following equation,

$$EU\left(\prod_i\right) \equiv EU\left[\prod_i \mid f\left(m_i, k_i, \omega, d_{ij}\right), f\left(m_j, k_j, \omega\right)\right]. \tag{3}$$

E denotes the expectation operator, *U* is the von-Neuman-Morgenstern utility function; m_i and k_i denote bean farming household inputs decision; m_j and k_j are the inputs decision of neighboring farming households, which in turn are a function of the social geographic distance *d*; and ω denotes environmental conditions. To control for endogenous group effects, as well as a contextual effect, we used a spatial weight matrix *W* that contains elements W_{ij}. This matrix captures the network structure of bean farming households in our survey sample. The weight matrix specification is based on inverse distance between a household and each of its *k* (13) nearest neighbors. The information stored in the weight matrix is row-standardized so that row sum of the weight matrix equals to one. Section 2.5 provides more details on the specification of the spatial weight matrix *W*. In this article, we focus on the case that *W* is row-normalized. Row-normalization is common in empirical studies of social interaction so that *WY* can be interpreted as the weighted average outcome of smallholder farming households across all neighbors of a given household (Lee et al., 2010).

If the expected marginal benefit is greater than the marginal benefit of growing traditional bean varieties, small farmers will plant IBB varieties. However, the expected marginal benefit is unobservable. In this special case, the discrete choice model becomes useful. They are commonly used to investigate a wide range of areas in agricultural economics, including technology adoption and land-use decision-making. We start from the basic empirical model, which is based on farming households' decisions on whether to grow an IBB variety.

A bean farming household's expected profit from growing an IBB variety, as opposed to a regular bean variety, depends on a set of different variables. These variables include prices of inputs and outputs; fixed factors such as farm assets and land holdings; soil characteristics; socioeconomic characteristics such as education and wealth; neighborhood influences (expected profits to neighbors from adoption); and factors on the supply side, such as planting material availability in the market.

The latent regression model is shown in Equation (5). We analyze the outcome of a discrete choice as a reflection of an underlying regression function. The basic theory is that the farmer makes a marginal benefit or marginal cost estimation based on the utility achieved (Greene, 2012). Note that the expected utility in the maximization problem is a function of profit in the first layer of the composite function and the marginal utility of profit is positive. We model the difference between benefit and cost as an unobserved variable, $y_i^* = \pi_{1i}$ - π_{0i}, which represents the difference in benefits where π_{1i} represents the benefits associated with IBB variety, and π_{0i} the benefits from other regular bean varieties, such that

$$y_i^* = G_i\beta + \in_i, \in_i \sim N(0, \sigma_\in^2). \tag{4}$$

We assume that ε_i has a mean of zero. Our only observation of the data generation process is

$$y_i = 1 \; if \; y_i^* > 0$$
$$y_i = 0 \; if \; y_i^* < 0. \tag{5}$$

The smallholder farming household either grows ($Y = 1$) or does not grow ($Y = 0$) an IBB variety in season B of 2015. However, smallholder farming households have a choice to decide how to grow a new variety. For instance, a farming household may plant all bean areas on all farming plots or a share with IBB in one or multiple farming plots. Since there are no farming households that plant the whole farm in only one crop, or one variety, the fraction of available land that is planted with IBB is not relevant in this study. We hypothesized that a set of intrinsic factors such as farmer and plot characteristics as well as environmental factors gathered in a vector G, explain smallholder farming households' decisions, so that:

$$Prob\,(Y = 1|G) = F(G, \beta)$$
$$Prob\,(Y = 0|G) = 1 - F(G, \beta). \tag{6}$$

The set of parameters βreflects the impact of changes in G on the probability. For instance, the marginal effect of a household's head age on the likelihood of adoption of IBB may be a factor of interest. Typically, the estimation of $P(G) = Pr(C = 1 \mid G)$ is done by means of a nonspatial probit (NSP) or nonspatial logit model.

We extend the basic choice model to a social interaction choice model. Manski (1993) developed a framework that describes social interaction in three tenets: (1) endogenous interactions, wherein the propensity of an IBB grower to behave in some way varies with the behavior of her/his neighbors; (2) contextual interactions, wherein the propensity of an IBB grower to behave in some way varies with exogenous characteristics of his/her neighbors; (3) correlated effects, wherein smallholder farming households in the same group tend to behave similarly because they have similar individual characteristics or face similar institutional environments.

The social interaction model we employed accounts for endogenous and contextual effects. First, the endogenous effect measures the interdependence across bean farming households with regard to IBB adoption decisions. In more detail, this interdependence refers to how expectations, preferences, knowledge, or constraints of one smallholder farming household are directly and indirectly influenced by the choices of other smallholder farming households and vice-versa in their communities. The endogenous effect aims to capture the process by which an individual farmer learns from his/her neighbors' decisions and outcomes of the decisions such as yields and profits. The IBB grower might then condition his/her target inputs for differences between his/her own and his/her neighbors' observed characteristics when learning from them (Munshi, 2004). By learning from others (typically neighbors), a new grower updates her priors about the unfamiliar technology and adds information on expected net returns in the optimal (profit-maximizing) problem of his/her adoption choices (Conley & Udry, 2010; Foster & Rosenzweig, 1995). In this respect, the prospect and effectiveness of social learning declines with geographical distance (Fafchamps, 2010). Comola et al. (2021) further confirmed the role of neighbors and distance. The statistical evidence of spatial dependence then can inform us about the degree of interdependence between decisions to grow IBB by one smallholder farming household and those of his/her neighbors. Second, the peer contextual effect measures which characteristics of neighbors might influence a smallholder farming household's decision to adopt IBB. Many published studies describe the role of neighbors' characteristics on a farmer's decision to adopt new agricultural technology. Ellison and Fudenberg (1993) use this argument to justify simple rules of thumb where farmers learn from similar neighbors' choices and the payoffs of these choices. A panel study by Foster and Rosenzweig (1995) shows the importance of learning by doing and learning from others in the adoption and diffusion of high yielding varieties (HYV) during the Green Revolution in India.

This seminal work shows that lacking knowledge about the management of the new technology is a barrier to adoption. Their research also identified that a farmer's own experience and neighbors' experience with HYV significantly increased the profitability of HYV. Conley and Udry (2010) provide empirical evidence that spatial closeness is correlated with the presence of information links. They report that novice farmers are more likely to change their inputs in the direction of inputs associated with positive outputs by their information neighbors. Our basic premise posits that IBB growers will communicate about their experience and the benefits of growing and consuming IBB. The cost of transferring this tacit knowledge to others is in increasing function of the social geographic distance between IBB growers and recipients of the knowledge. We define this social behavior with an old adage that goes "a close neighbor is more helpful than a relative far away." This assumption may be more accurately applied to smallholder farming households, who not only learn the profitability of the new technologies from their neighbors, but also learn the know-how to farm the new technology. A panel study of technology adoption in Ghana by Nourani (2019) reports that socially distant (weak ties) and proximate peers (strong ties) contribute to distinct objects of learning. Farmers' interactions with distant friends help to determine whether to adopt a new crop based on profitability beliefs, while proximate peers not only help to provide information on the crop profitability but also share knowledge of how to cultivate the new crop. Granovetter (1973)'s strength of weak ties claims that interpersonal networks provide the most effective micromacro bridge between small-scale interaction and large- scale patterns. Learning about new technology, such as growing IBB varieties, sheds light on the uncertainty of its profitability as well as involves acquiring information about how to optimally manage the new technology (Foster & Rosenzweig, 2010). We use farming experience and management indicators as indicators of tacit knowledge. We assume farmers' tacit knowledge to vary with their cognitive, social, cultural, farming experience, and economic local conditions as well as with their local and external interactions. The exogenous matrix W is then used to empirically test the extent of spatial interdependence between farmers' decisions as well as spillover effects.

As discussed in Ward and Pede (2015), contextual effects may also influence the adoption of IBB varieties. A smallholder farmer's behavior might be affected by the personal characteristics of proximate peers. For example, the socioeconomic characteristics of neighboring bean farmers, such as their household size and education level, may have a positive impact on the farmers' IBB adoption behavior. If contextual effects are controlled for and coefficient estimates associated with peer effects do not change, then we can conclude that the adoption of IBB is conditioned not only by peer effects but also by contextual factors of neighboring smallholder farmers (Durlauf & Ioannides, 2010; Ward & Pede, 2015).

2.2 | Spatial econometrics

In this model, we test two hypotheses, whether the propensity of an individual farming household to grow a new IBB variety depends on (1) the prevalence of IBB adoption of neighboring farming households and (2) on the prevalence of the distribution of the characteristics of neighboring farming households. In spatial econometrics, social interaction is operationalized by constructing a spatial structure that defines the interdependences among farming households in which preferences, local knowledge, and constraints faced by one farming household are directly influenced by the characteristics and choices of other farming households. We use spatial econometric theory on Bayesian spatial probit modeling presented by LeSage et al. (2011) and J. LeSage and Kelley Pace (2009).

The general model for social-spatial interaction takes the following (matrix) form:

$$y \;=\; \rho W y +\; \beta_1 X +\; \beta_2 W X + u. \tag{7}$$

$$u \;=\; a +\; \lambda W u +\; \varepsilon. \tag{8}$$

where the matrix $W\ (n \times n)$ called the spatial weight matrix, captures the dependence structure between neighboring farming households. y denotes a $N \times 1$ vector consisting of one observation on the dependent variable for every unit in the sample ($i = 1, ..., N$). The variable Wy denotes the endogenous interaction effects among the dependent variables across neighboring farming households, X is an $n \times k$ matrix of observations on exogenous variables, WX denotes the exogenous interaction effects among the independent variables, and Wu the interaction effects among the disturbance terms of the different spatial units. ρ is called the SAR coefficient, λ is the spatial autocorrelation coefficient of the disturbance term to capture remaining exogenous spatially correlated effects, a represents an $n \times 1$ vector of fixed but unknown parameters to be estimated, while β_1, just as for β_2 is an $n \times k$ matrix of unknown parameters to be estimated.

For the first hypothesis, we test the endogenous effect which is also described in the literature as imitation, contagion, bandwagons, social norms, and "keeping up with the Joneses." Similar to the standard probit and logit model as presented in Section 2.1 above, where y_i^* represents the latent unobservable utility that depends not only on observable determinants of household i represented by X, SP modeling also depends on the latent utility of the neighboring household y_j^*. Restrictions $\beta_2 = 0$ and $\lambda = 0$ give rise to the SAR model. $(I - \rho W)^{-1}$

In more detail, the SAR model, as suggested by J. LeSage and Kelley Pace (2009), is

$$y_i^* \;=\; \rho W y_j^* +\; \beta X +\; \varepsilon,\; \varepsilon \sim N\left(0, I_n\right). \tag{9}$$

The data generating process for y_i^* is

$$y_i^* = \left(I_n - \rho W\right)^{-1} X\beta + \left(I_n - \rho W\right)^{-1}\varepsilon, \varepsilon \sim N\left(0, I_n\right). \tag{10}$$

where $(I - pW)^{-1}$ is the "Leontief inverse" that links the decision of the smallholder farming household y_i^* to all the X in the system through a so-called spatial multiplier (Wilhelm & Godinho de Matos, 2013).

For the second hypothesis, we model the effect of contextual factors on smallholder farming households' decision to adopt IBB planting material. We employ a variation of the SAR model in the analysis of contextual effects—the Bayesian SDM. This model allows variables from neighboring farming households contained in the matrix X to exert an influence on the propensity of IBB adoption by household i. This is accomplished by adding average-neighbor values of the explanatory variables, created using the matrix product WX (Anselin, 1988; Anselin & Rey, 2014; J. LeSage & Kelley Pace, 2009).

J. LeSage and Kelley Pace (2009) provides the data generation process of the SDM as

$$y_i^* = \rho W y_j^* + \alpha_1 + \beta_1 X + \beta_2 W X + \varepsilon, \varepsilon \sim N(0, I_n). \quad (11)$$

The spatial lag latent dependent variable Wy_j^* involves the $n \times n$ spatial weight matrix W that contains elements consisting of either one or zero. All elements of the matrix W are row standardized (non-negative and each row sums to 1). The scalar parameter ρ measures the strength of dependence, with a value of zero indicating independence. A NSP model emerges when $\rho = 0$.

The expression in Equation (7) is the best option to test for full spatial interaction effects. However, in order to identify the endogenous and exogenous interaction effects, which are the ones of our interest in this research, excluding the spatially correlated effect is the best option (Elhorst, 2010; Manski, 1993). If both hypotheses, $\beta_2 = 0$ and $\beta_2 + \rho\beta_1 = 0$, stated above are rejected, the SDM is the best model to describe the data generating process and also produce unbiased coefficient estimates (Elhorst, 2010). Interpretation of the marginal effects are presented in Appendix A.

2.3 | Multilevel model

As a robustness test, we ran a new set of regressions with fixed and random effects. To do so, our multilevel data structure included villages in the upper level and smallholder farming households nested within villages. Multilevel models are useful to account for intervillage variations in the data via estimation of the variance of random effects (Bivand et al., 2017). We carried out a multilevel Bayesian analysis of latent Gaussian models using the Integrated Nested Laplace Approximation (INLA) (Rue et al., 2009). In a sample of villages, the model with fixed and random effects treats observations from a given village as a cluster, and assumes a random effect for each cluster (Goldstein, 2003). We define $\mu_{iv} = (Y_{iv}|U_v)$. Let Y_{iv} be the response of smallholder farming household i village v, $i = i_1, \ldots, n_v$. In our case, the responses are adoption of IBB planting material. We implemented *i.i.d* random effect term U at the upper village level. The *i.i.d* random effect representation implies (1) strong intravillage dependence between the outcomes of lower-level observations here smallholder farming households and (2) independence between the village random effects. The general mixed model has the form,

$$g(\mu_{iv}) = \gamma X + U_v;\ i = i_1, \ldots, n_v; v = 1, \ldots, 81; u_v \sim N(0, \tau_u). \quad (12)$$

g is the link function, for binary outcomes is the logit link. X_{iv} denotes a vector of explanatory variables such as household head age, years of farming experience, household size, wealth index, and the number of bean varieties cultivated, for fixed-effect model parameters γ. U_v denotes the vector of random effects for village v. This is common to all observations in the cluster. Note that n_v represents the number of smallholder farming households in village v. Village v is indexed from 1 to 81. The random effect vector U_v is assumed to have a multivariate normal distribution N $(0, \tau_u)$. The covariance matrix τ depends on unknown variance components and correlation parameters. Parameters pertaining to the random effects can also serve as a useful summary of the degree of heterogeneity of the population of smallholder farming households.

In sum, multilevel modeling aims to distinguish between two types of spatial dependence: vertical and horizontal (Dong & Harris, 2015). The former refers to the process in which the outcomes of lower-level units, that is, smallholder farming households nested in villages, are correlated because they are affected by the same factors. Horizontal dependence is associated with spatial econometrics, which arises from the social interaction or spillover effects among spatial entities due to geographic proximity. The parameters pertaining to the random effect are of interest as useful summary statistics of the degree of heterogeneity of smallholder farming households. We expect the random effect to reveal a spatial relationship at the village level. For instance, villages located close to each other will tend to be more similar compared to villages located farther away. Studies on agricultural technology adoption show that smallholder farming households located closer to midsize or large market centers may have similar characteristics, such as access to agricultural inputs. Farmers located further away from these market centers may gradually change from being peri-urban to smallholder farmers with intrinsic characteristics of remote rural areas.

2.4 | Data and descriptive statistics

The data to conduct this research comes from an adoption assessment study conducted in Rwanda in season B of 2015. The main aim of the survey is to investigate the adoption of iron bean varieties among Rwandan bean farmers. Data collection was split into two parts: a listing survey and a household survey. The former was conducted at the beginning of season B of 2015, where 19,575 households were listed in 120 randomly selected villages, from a master sample of 3,390 villages (representing 14,000 villages in the country) of which 93% were bean growers. The sampling frame for the second survey was derived from the former. Equal probability sampling was used to randomly select 12 households in each of the 120 villages, and 1,397 bean-farming households were interviewed (Asare-Marfo et al., 2016). The survey instrument consisted of 12 modules; we used data from eight out of 12 to run all statistical analyses. These modules include information on household roster, plot characteristics, bean production, bean varietal traits, iron bean adoption history, household assets, and housing characteristics.

Sources of IBB planting materials varied. About 40% of IBB growers obtained their seed either from local markets, HarvestPlus marketing mechanisms, or through RAB extension services and NGO's. One third of IBB growers recycled IBB seed from previous seasons, while 27% of IBB growers received planting material from friends, neighbors or relatives. Results from our spatial econometric models show significant interdependence between bean farmers' decisions to adopt IBB. The scalar ρ measures the degree of spatial diffusion among IBB growers. The scalar ranges from .25 to .42 suggesting that in addition of the direct beneficiaries the biofortification program spillover indirect beneficiaries to grow IBB.

The high intensity of IBB adoption in the eastern region has been propelled in part by the high density of delivery systems that enhance access to IBB seed to smallholder bean farmers, as shown in Figure B2 (see Appendix B). For practical purposes of our analysis, we rescaled the density map to squares of 10 km × 10 km. Therefore, the density values are reported as the number of points or delivery venues per 100 square kilometers. We observe a high density of delivery mechanisms on the Eastern region with lower density values over the Northern region.

Table 1 reports descriptive statistics by adoption status for the most important characteristics of the 1,394 interviewed bean growing households in 2,516 plots and 3,017 subplots. Of these households, 36% cultivated only bush beans, 44% cultivated only climbing beans and 20% cultivated both bush and climbing beans. Bush and climbing bean adopters come from two different data generating processes. Climbing beans grow tall and need a stake for support with a yield potential (biologically) of four tons per ha, while bush beans grow about two to three feet tall and do not require support with a yield potential of three tons (biologically) per hectare. These differences are the main reasons we set-up different econometric models for them.

2.5 | Specification

We used the nomenclature M1 and M2 for the two specifications used for each of the NSP and SP models as specified in Subsections 2.1 and 2.2, respectively. Specification M1 aims to test how household characteristics such as wealth (proxied by a household asset index - see Appendix C), household composition, iron bean consumption, and years of farming experience play a role in IBB adoption. In addition, it explores the role of a number of varieties used to manage the risk of food insecurity due to crop failure brought on by drought. Specification M2, on the other hand, looks at the importance of household technical capacity measured through the management index in connection with the education level and household size. The independent variable in this study may be also spatially correlated between villages. For instance, villages occupying the same soil type may share similar soil characteristics. As a proxy of soil quality, we used the slope of the farming plots. The latent variable for the adoption of IBB corresponds to the unobserved profitability. For the construction of the spatial weight matrix, we determine a k nearest neighbor in conjunction with an inverse bilateral distance.

The specification of the covariates is key and in line with economic theory. Table 1 shows relevant factors driving IBB adoption that include household characteristics, farm characteristics, management practices, and regional geographic variables. We combine the row-normalized adjacency weight matrix with the inverse distance weight. Thus, if for every one smallholder farming household there are other k other smallholder farming households, then each weight will be $W_{ij} = \frac{\frac{1}{d_{ij}}}{\sum_{k \neq j} \frac{1}{d_{ij}}}$. Previous research by J. Lesage and Pace (2014) shows robust estimates on the true partial derivatives (effects) and the spatial autocorrelation to different spatial weight matrices, such as nearest neighbors, inverse distance with decay influence based on a cut-off distance, and/or the number of neighbors. We found similar results to these findings. Models differing only in W yielded similar impacts (partial derivatives).

In Rwanda, more than 80% of the economically active population is involved in agriculture. In this study, on average, households with more economically active

TABLE 1 Characteristics of adopters and nonadopters of IBB in Rwanda

Variables	Non-adopters	HIB adopters	*p*-level*
Household characteristics			
Number of women 12–49 years old	2.03	2.22	.00
Number of individuals 0–19 < = > = 65 years old	2.77	2.92	.12
Number of people per household	4.80	5.14	.01
Dependency ratio (children)	1.39	1.43	.51
Number of individuals per household - Economic active population [18–65]	2.68	2.93	.00
Female household head (proportion of households)	.27	.26	.66
Number of male members per households	2.22	2.54	.00
Age of household head (years)	46.77	46.83	.94
Level of education (average number of years in education per household)	2.82	3.46	.00
Wealth Index	.42	.47	.00
Years of farming experience	8.10	7.13	.07
Farm characteristics and management practices			
Number of crops	1.78	1.87	.08
Number of plots	2.97	3.34	.00
Number of varieties	2.44	4.34	.00
Percentage rented in land	13.97	11.06	.08
Percentage own title	70.24	73.45	.18
Percentage no title	13.17	14.07	.63
Percentage share cropping	1.81	.86	.08
Total farmland (m^2)	2369.91	3092.79	.00
Management index	.39	.45	.00
Weighted plot slope (percent)	12.87	12.25	.19
Land labor ratio (m^2/person)	998.82	1153.23	.08
Time to plot (minutes)	15.45	15.36	.94
Land terraced (proportion of households)	.22	.26	.13
Plot irrigated (proportion of households)	.06	.09	.08
Hired labor (proportion of households)	.35	.49	.00
Applied fertilizers (proportion of households)	.20	.26	.03
Applied manure (proportion of households)	.77	.86	.00
Applied compost (proportion of households)	.59	.66	.02
Applied pesticide (proportion of households)	.09	.10	.56
Bean area m^2 (proportion of households)	1545.58	1927.93	.00
Bean consumption (proportion of households)	.06	.09	.00
Weighted average yield (kg/ha)	850.18	870.44	.54
Access to credit (proportion of households)	.21	.20	.54
Geography			
Kigali region (proportion of households)	.02	.02	.81
Southern region (proportion of households)	.27	.28	.80
Western region (proportion of households)	.26	.16	.00
Northern (proportion of households)	.21	.20	.54
Travel time (minutes) to cities equal or greater than 50,000 inhabitants	248.80	254.65	.54
DEM (meters)	1734.27	1658.07	.00
Drought index	−.03	−.03	.70
Number of observations	962.00	432.00	

*We are testing that the mean difference is zero and is a difference *t*-test *p*-value.

members have a higher propensity to adopt IBB, suggesting that available labor is a consideration in the decision to adopt. The difference in the average household family size is statistically significant between adopters and nonadopters, suggesting the need to meet food demand in the household.

The average education of household members that grew IBB is statistically greater than for nonadopting households, indicating that higher education influences the adoption of new technology and is positively correlated with wealth. Three mechanisms related to human capital have been identified in the literature to explain the technology adoption: (1) more educated agents are wealthier and thus, the education–adoption relationship represents an income effect; (2) more educated agents have better access to information; and (3) more educated agents are better able to learn/internalize new information. The last mechanism has always been the focus of economists (Foster & Rosenzweig, 2010). Numerous studies find a significant relationship between education indicators and farm productivity. Since the adoption of innovation generally increases productivity, the importance of education in affecting adoption behavior is implicit. Jamison and Moock (1984) test the effect of schooling and extension contacts on the adoption and diffusion of agriculture technology in Nepal. They find that schooling influences adoptive behavior, but that household income mediates the adoption decision. Weir and Knight (2007) find that household-level education in Ethiopia is an important factor in adoption, and that early adopters tend to be more educated and to influence their neighbors. Giné and Yang (2009) find that farmers' education, income, and wealth were positively correlated with the take-up of insured loans to adopt a new crop technology in Malawi.

Adopters managed more plots and varieties over larger cropped land areas. These behaviors could be associated with a household's food security strategy where households use mixed bean seeds (local, improved, and iron-biofortified) to reduce the risk of food insecurity related to crop failure or poor crop yield performance of a specific bean variety.

Adopters own larger farmland. The size of the farm may have different effects on the adoption rate, depending on the characteristics of the technology. A wide variety of empirical results interpreted in the context of the theoretical literature suggests that farm size is a proxy for many potentially important factors, such as access to credit, capacity to bear risk, access to scarce inputs, wealth, and access to information (Foster & Rosenzweig, 2010; Hall & Khan, 2003).

In this study, we found that land ownership affects the adoption of IBB. A number of empirical and descriptive studies have also considered the effects of land tenure arrangements (which is often considered to be a good proxy for wealth), and the proportion of farms rented on the adoption of new agricultural technology, such as improved, high-yielding varieties. Findings suggest that the form of land tenure (e.g., renters, sharecroppers, landowners) may affect the adoption decisions and diffusion rates. Shiferaw and Holden (2005) investigated the adoption of plot level land conservation practices in Ethiopia and did not find the tenure regime for a plot to have a significant effect on adoption.

About 27% of IBB growers received planting material from friends or relatives. The characteristics of a social network—a farmer's social links through which information, goods, money, and services flow—are factors that might induce technology adoption and diffusion (Maertens & Barrett, 2013). Krishnan and Patnam (2014) find evidence that social learning was more persistent than learning from extension services for the adoption of new varieties and fertilizer in Ethiopia. Conley and Udry (2010) examine how learning from the experience of others and the flow of information depends on the structure of social networks when there is no access to agricultural extension services. Foster and Rosenzweig (1995) find that farmers with neighbors who have more farming experience have higher profits than those without such neighbors. Ward and Pede (2015) found that the neighbor effect is an important determinant of the use of hybrid rice.

As a proxy of household economic well-being and technical capacity, we used the wealth index and the management index, respectively (see Appendix C). Adopters were wealthier, more technical in their crop management practices, and experienced higher yields. Households located in the Northern Province on average had the highest management index, followed by the Western and Southern provinces. Management practices refer to the methods bean farmers use to increase productivity. Households in the city of Kigali or Central region were on average wealthier than farmers from other regions. The second-wealthiest rural households were located in the Western region, followed by households in the Northern region. There are fewer wealthy families in the southern and eastern regions.

We used the slope of the cultivated land as an indicator of soil quality. On the one hand, soils with an increasing slope gradient tend to be shallower with undesired properties such as an increased potential for surface erosion. On the other hand, soils on less steep terrain tend to accumulate sediments, have a more complex soil structure, and retain soil moisture (FAO, 2000). We expect growing conditions to be positively spatially correlated across neighboring farming households. In addition to climate variables (rain and temperature), soil types and topographic characteristics are likely to not only be shared among nearby farming households but also vary across villages.

We included regional geographical variables to control for the disparities in the quality of road infrastructure and accessibility to extension services. Travel time to extension services and medium-sized cities is a measure of geographic accessibility. Access is defined as the time needed to travel from a specific household to the nearest location of interest. Good transportation is associated with the diffusion of technology, better access to inputs, and lower transportation costs. Travel time is estimated using an algorithm that factors road quality, speed, slope, and biophysical characteristics. A detailed explanation for estimating access to markets is presented by Ulimwengu et al. (2009, p. 15).

For model comparison, we estimated the log-likelihood as a measure of fit adjusted for model complexity. We also reported two information criteria, the Bayes (Schwarz) information criterion (BIC) and the Akaike information criterion (AIC) measures. To compare the multilevel and the spatial Bayesian models, we estimated measures of complexity and fit such as the model's deviance information criterion (DIC). Smaller values of the DIC indicate a better trade-off between complexity and fit of the model. The Watanabe–Akaike information criterion (WAIC), also known as the widely applicable Bayesian information criterion, is similar to the DIC but the effective number of parameters is computed in a different way. See Watanabe (2013) and Gelman et al. (2014) for details.

3 | RESULTS AND DISCUSSION

3.1 | Spatial econometric analysis: adoption model estimates (NSP vs. SP models)

The coefficient estimates (posterior means, standard deviations, and Bayesian p-levels) of the two specifications (M1 and M2) for two spatial models (SAR and SDM) and a NSP model are shown in Tables 2 and 3, while Tables 4–7 and 8–11 show the estimated average marginal effects. Tables 4–7 and 8–11 are the basis for inference regarding the effect of changes in the various independent variables on the probabilities that bean farmers will adopt IBB and on the spatial spillover effect on neighboring bean farmers. We also tested the robustness of our results. Table E1 shows posterior means (standard deviations) of a multilevel spatially structured fixed and random effects model.

For each scenario, we use a standard generalized linear model (GLM) probit model and two SP models. We describe and compare the average marginal effects for each model. There are four common covariates in both specifications: number of children in the household, the number of varieties, age of household head, and accessibility to extension services. The specification M1 aims to test how household characteristics, such as wealth (based on an asset-based wealth index as explained in Appendix C), household composition, and years of farming experience, play a role in IBB adoption. In addition, the M1 scenario explores the role of the number of varieties (excludes IBB varieties) used to manage the risk of food insecurity due to crop failure caused by drought. The specification M2, on the other hand, looks at the importance of household management technical capacity measured through a management index in connection with education level and household size (see Appendix C). M2 does not include the wealth index because of its positive correlation with the management index and education level.

For all NSP models, we computed and reported a diagnostics test (Kelejian-Prucha (error)) for spatial dependence. The diagnostic tests for all probit models were positive and significant; therefore SP models are used to calculate the probability, $P(x) = Pr(D = 1|X)$, or propensity, of being an IBB grower for each observation. We only report the marginal direct and indirect effects of the SP model. Models are compared using log-likelihood and information criteria, such as AIC and BIC (Schwartz' Bayesian Information Criterion). For model comparison using the log-likelihood value, models with log-likelihood values closer to zero are considered better models. While for model comparison using the information criteria, models with smaller values of these criteria are considered better models. We reported the DIC values to compare the spatial models, as estimated using Bayesian methods. Lower DIC values indicate a better fit for Bayesian models. We also reported the Raftery–Lewis diagnostics for each specification. We reported the diagnostic statistics based on a 95% interval using .05 and .95 quantiles with the desired accuracy equal to .02. Table D1 (see Appendix D) shows the Raftery–Lewis diagnostics. The "Lower bound" column represents the number of draws that would be required if the draws represented an *i.i.d* chain. The "Total" column indicates the total number of draws needed to achieve the desired accuracy for each parameter. The i-statistic presents the ratio of the "Total" to the "Lower bound" column. For the bush bean specifications, the total number of draws ranges from 394 to 632 draws, which are the number of draws required to achieve the desired accuracy for each parameter. For the climbing bean specifications, the total number of draws ranges from 407 to 591 draws. In the last column of Table D1 according to Raftery and Lewis (1992), an i-statistic exceeding five is indicative of convergence problems with the sampler. In the specifications for both climbing and bush bean growers, the i-statistics is below this theoretical threshold.

SP models, such as SAR and SDM, allowed us to disentangle the total marginal effect into direct and indirect

TABLE 2 SAR, SDM, and GLM probit model estimate for bush bean farmers

Variables	M1.SAR	M1.SDM	M1.NSP	M2.SAR	M2.SDM	M2.NSP
Rho	.3088***	.2976***		.4238***	.3845**	
	(.0912)	(.079)		(.0908)	(.1014)	
Constant	−5.1800	−7.663	−3.9980	−5.1349	−4.4040	−1.5507***
	(8.918)	(9.3890)	(8.9410)	(8.0632)	(8.0910)	(.3252)
Household (HH) size				.0047	.0009	.0779***
				(.0385)	(.0384)	(.0293)
Number of economic active males in HH	.1709**	.1709***	.1606**			
	(.0634)	(.0635)	(.0614)			
Number of children under 5 years old in HH	−.1666	−.1676**	−.1658**	−.1422	−.1378	.0048
	(.1095)	(.0995)	(.1025)	(.1012)	(.1012)	(.0919)
Log (HH head age)	2.646	3.9860	1.9350	2.6797	2.7694	1.7640
	(4.769)	(5.0620)	(4.8100)	(4.3147)	(4.3155)	(4.0634)
(Log (HH head age)) ^{2}	−.4794	−.6666	−.3776	−.4016	−.4119	−.2210
	(.634)	(.6783)	(.6441)	(.5697)	(.5699)	(.5329)
HH average years of schooling				.0237	.0266	.0961***
				(.0398)	(.0413)	(.0315)
Wealth Index (0-1)	.4080	.3771	.3103**			
	(.5133)	(.5268)	(.4946)			
Number of varieties cultivated	.3091***	.3106***	.2930***			
	(.0423)	(.0420)	(.0408)			
Farming experience (years)	.0381***	.0391***	.0355***			
	(.0102)	(.0112)	(.0103)			
Share of land area with legal title				.0016	.0013	−.0014
				(.0014)	(.0015)	(.0014)
Management Index (0-1)				.7176**	.8117**	.5630**
				(.2989)	(.2927)	(.2795)
Weighted plot slope				−.0002	−.0004	.0002
				(.0085)	(.0091)	(.0080)
Land labor ratio (m^2/person)	−.0001	.0002	-.0001			
	(.0001)	(.0001)	(.0001)			
Travel time to extension services >1 h	−.0088	.0941	−.0011	.0167	.1237*	−.0110
	(.0222)	(.0829)	(.0227)	(.0175)	(.071)	(.0205)
Planting material from friends or relatives	10.1000***	17.1600***	26.1100			
	(3.0200)	(4.2730)	(803.800)			
W-HH size					.020	
					(.070)	
W-Number of males in HH		.0810				
		(.1347)				
W-Number of children under 5 years old in HH		−.1221			−.3295*	
		(.1868)			(.1873)	
W-Log (HH head age)		−.0085			−.0147	
		(.0127)			(.0089)	
W-HH average years of schooling					−.0932	
					(.0759)	
W-Wealth Index		.6714				
		(1.0120)				

(Continues)

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists

TABLE 2 (Continued)

Variables	M1.SAR	M1.SDM	M1.NSP	M2.SAR	M2.SDM	M2.NSP
W-Number of varieties cultivated		.1082				
		(.0764)				
W-Farming experience (years)		.0115				
		(.0206)				
W-Share of land area with legal title					.0029	
					(.0027)	
W-Management Index					.1522	
					(.5734)	
W-Weighted plot slope					.0382**	
					(.0148)	
W-land labor ratio (m^2/person)		−.0002**				
		(.0001)				
W-Travel time to extension services >1 h		−.1066			−.0096	
		(.0854)			(.0712)	
W-Planting mat. From friends or relatives		−1.8440*				
		(1.0020)				
Kelejian-Prucha (error)			3.987***			4.618***
Log likelihood	−205.4803	−197.3877	−211.0308	−294.6993	−289.8208	−294.343
BIC	486.6358	519.3199	569.6778	653.8916	685.4927	644.7248
AIC	435.9174	434.7892	444.06	611.6262	613.6415	606.686
DIC	434.650	432.310		594.54	597.370	

Note: () are standardized errors. *, ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

impacts. Direct effects and indirect effects are different among smallholder farming households. The direct effect measures how a change in an explanatory variable in household i affects the dependent variable in household i, plus any feedback effects. The indirect effects measure how changes in the explanatory variables associated with household i cumulatively impact the dependent variable in all other households with a decaying effect for farmers located farther away. These effects are referred to as spatial spillovers. The statistically significant spatial autocorrelation coefficient ρ, on the endogenous lagged dependent variable in the SAR and SDM models, measures the strength of spatial interdependence in smallholder farming households' decisions regarding adoption of IBB. The case of the SDM interaction model assumes that an individual smallholder farming household is equally influenced by neighboring farming households, so that the endogenous and contextual effects are specified as the average outcomes and characteristics of the peers, respectively.

In Tables 2 and 3, the scalar parameter rho (ρ) is different from 0 and statistically significant at 1%. Its magnitude varies from .30 to .42, suggesting significant interdependence in smallholder bean farming households' decisions regarding the adoption of IBB varieties as well as spatial spillovers. In the context of spatial models when $\rho = 0$, the interpretation of the marginal effect of a one-unit change in x on y, ceteris paribus, is no longer valid. For the SDM models[1], the results for the total, direct, and indirect effects depend on two-parameter vectors β_1 and β_2. In this particular case, spatial spillovers are a function of (1) the location of bean farming households, (2) the social geographic distance between bean farming households captured by the element W_{ij}, (3) the parameter rho that measures the degree of spatial interdependence in smallholder farming households' decisions, and (4) the magnitude of the coefficients for β_1 and β_2. Moreover, for the SDM models, the indirect effect is divided into two parts: the local effects due to the β_2 coefficient, and the global effects arising from the inverse matrix involving ρ. The first effects are local because their impact is on immediate smallholder farming households, if the element W_{ij} of the spatial weights matrix is nonzero which implies contextual effects. The second effects are global influence because affect all bean farmers through the spatial multiplier $(I - \rho W)^{-1}$, where

[1] When running the Spatial Durbin Model (SDM), it is important to note that the coefficients of the lag variables for farming experience and the management index are not significantly different from zero. Therefore, these outcomes should not be treated as a rejection to the existence of spatial spillovers. Instead, inferences should be made on the estimates of the cumulative effects (partial derivatives) described in Appendix A

TABLE 3 SAR, SDM, and GLM probit model estimate for climbing bean farmers

Variables	M1.SAR	M1.SDM	M1.NSP	M2.SAR	M2.SDM	M2.NSP
Rho	.2542***	.2832*		.4172***	.4162**	
	(.0841)	(.0943)		(.0995)	(.0967)	
Constant	−1.3800	−3.099	−1.9070	−4.1959	−3.6150	−4.9466***
	(8.3210)	(8.746)	(8.394)	(7.4189)	(7.7029)	(7.6498)
Household (HH) size				.0743***	.0768***	.0700***
				(.0354)	(.0345)	(.0334)
Number of economic active males in HH	.0497	.0467	.0391			
	(.0581)	(.0577)	(.0577)			
Number of children under 5 years old in HH	−.0083	.0080	−.0010	.0026	.0321	.0167
	(.0901)	(.1004)	(.0943)	(.0992)	(.1020)	(.0952)
Log (HH head age)	−.8866	.1090	−.5477	1.5313	1.3905	1.7640
	(4.4330)	(4.6530)	(4.4750)	(3.9432)	(4.0670)	(4.0634)
(Log (HH head age)) ^{2}	.2175	.0767	−.1585	−.1929	−.1703	−.2210
	(.5893)	(.6178)	(.5949)	(.5162)	(.5328)	(.5329)
HH average years of schooling				.0966***	.0976***	.0961***
				(.0314)	(.0324)	(.0315)
Wealth Index (0-1)	.9898**	1.1840**	1.0720**			
	(.4710)	(.4810)	(.4646)			
Number of varieties cultivated	.2262***	.2340***	.2198***			
	(.0389)	(.0399)	(.0382)			
Farming experience (years)	−.0434**	−.0374***	−.0351**			
	(.0168)	(.0158)	(.0164)			
Share of land area with legal title				−.0013	−.0008	−.0014
				(.0014)	(.0014)	(.0014)
Management Index (0-1)				.4921*	.5202*	.5630**
				(.2726)	(.3093)	(.2795)
Weighted plot slope				−.0098	−.0127*	−.0097
				(.0067)	(.007)	(.0068)
Land labor ratio (m^2/person)	.0000	-.0001	-.0001			
	(.0001)	(.0001)	(.0001)			
Travel time to extension services >1 h	.0138	.0184	.0011	−.0057	−.0063	−.0110
	(.0207)	(.0791)	(.0227)	(.0196)	(.0501)	(.0205)
Planting material from friends or relatives	14.1900***	13.0500***	27.7300			
	(4.2260)	(3.6360)	(670.2000)			
W-HH size					.0443	
					(.0595)	
W-Number of males in HH		.1038				
		(.1138)				
W-Number of children under 5 years old in HH		−.3361*			−.1889	
		(.1856)			(.1779)	
W-Log (HH head age)		.0088			.0029	
		(.0114)			(.0088)	
W-HH average years of schooling					−.0214	
					(.0845)	
W-Wealth Index		−.9495				
		(.9019)				

(Continues)

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists

TABLE 3 (Continued)

Variables	M1.SAR	M1.SDM	M1.NSP	M2.SAR	M2.SDM	M2.NSP
W-Number of varieties cultivated		−.0219***				
		(.0698)				
W-Farming experience (years)		−.0211				
		(.0191)				
W-Share of land area with legal title					−.0039	
					(.0026)	
W-Management Index					.4490	
					(.4665)	
W-Weighted plot slope					.0214	
					(.0117)	
W-land labor ratio (m^2/person)		.0001				
		(.0001)				
W-Travel time to extension services >1 h		−.0060			−.0096	
		(.0804)			(.0678)	
W-Planting mat. From friends or relatives		.0082				
		(.8535)				
Kelejian-Prucha (error)			3.987***			4.618***
Log likelihood	−249.5146	−244.1141	−252.6889	−326.7116	−322.4651	−326.984
BIC	576.0496	623.0139	575.9799	712.0938	747.9928	711.7333
AIC	523.0293	530.2282	527.3779	672.3285	677.299	671.968
DIC	539.510	520.320		664.410	664.260	

Note: () are standardized errors. *, ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

the matrix W_{ij} is a peer matrix. This spatial multiplier indicates there is a global social multiplier in the system that indirectly affect nonbeneficiaries. Important to note that we assume the weight matrix is exogenous. The spatial connectivity matrix W serves as an appropriate instrument that allows identifying endogenous social interactions effect defined as Wy and exogenous or contextual effect WX. In other words, each pairwise interaction of smallholder farming households has an endogenous social effect of the contemporaneous influences of peers ρ and the exogenous effect includes characteristics of peers β_2. In the SAR models, these effects depend only on the first β parameter vector. The SAR models have a common multiplier for each variable. This global multiplier indicates that changes in a smallholder farming household's decision to adopt IBB will affect the decision of smallholder farming households everywhere. Also, important to note is that variables' values are not likely to be distributed independently. For instance, explanatory variables may exhibit spatial dependence.

Although we do not control for spatial fixed effects, Anselin and Arribas-Bel (2013) have shown through multiple simulations that when the data generating process is a SAR model, spatial fixed effects may be spurious. Their experiment also shows that spatial fixed effects only control for spatial correlation when the data generation processes correspond to a block structure which violates the principle of spatial interaction.

In general and comparing the absolute values of the coefficients, the SAR model's indirect effects are smaller than the direct effects. The SAR model's direct impacts were statistically indifferent from the direct effects of the NS probit model's direct impacts in terms of both sign and magnitude. Below, we provide a discussion of the average marginal effect for the SAR and SDM models.

3.2 | Bush bean analyses

Table 2 shows the results of M1 and M2 on bush bean varieties. We observe that the signs of some covariates are consistent in the SP models and NSP models. Farming experience, planting material from friends and relatives, the numbers of bean varieties cultivated, the management index, and the number of male members in the household have a positive influence on the propensity of adoption of IBB bush varieties, while the numbers of children in the household have a negative influence. In the next section, we will discuss in more detail the significance level, magnitude, and sign of the average marginal effect of each variable through summary measures of direct, indirect, and total effects.

TABLE 4 SAR and GLM probit model effect estimates for bush bean growers (M1)

Variables	Direct effect Lower .05	Coefficient	Upper .95	Indirect effect Lower .05	Coefficient	Upper .95	Total effect Lower .05	Coefficient	Upper .95	NSP
Number of economic active males in HH	.0159	.0381	.0610	.0043	.0166	.0340	.0221	.0547	.0890	.0372
Number of children under 5 years old in HH	−.0769	−.0372	.0050	−.0384	−.0159	.0020	−.1088	−.0532	.0060	−.0384
Log (Household head age)	−1.1110	.5962	2.3640	−.4598	.2556	1.1470	−1.5770	.8518	3.3680	.4483
(Log (Household head age))^2	−.3451	−.1078	.1200	−.1674	−.0464	.0450	−.4883	−.1541	.1730	−.0875
Wealth Index	−.0913	.0912	.2790	−.0404	.0371	.1280	−.1318	.1283	.3930	.0719
Number of varieties cultivated	.0558	.0690	.0830	.0115	.0298	.0540	.0756	.0988	.1290	.0679
Farming experience (years)	.0048	.0085	.0120	.0012	.0037	.0070	.0066	.0122	.0180	.0082
Land labor ratio (m^2/person)	.0000	.0000	.0000	.0000	.0000	.0000	−.0001	.0000	.0000	.0000
Travel time to extension services >1 h	−.0098	−.0020	.0060	−.0048	−.0009	.0020	−.0148	−.0029	.0080	−.0006
Planting material from friends or relatives	1.2690	2.2630	3.4650	.4327	.9070	1.4500	1.9730	3.1700	4.5550	6.0480

Tables 4–7 shows the significance level and marginal effect outputs for the NSP and SP models for bush bean growers. The first column lists all the variables used in each model specification. Columns with the headings direct, indirect effect, and total effect show the posterior means and their respective lower (5%) and upper (95%) bounds confidence intervals for the SAR SP model. The last column corresponds to the marginal effect of the standard NSP model, which is equivalent to the direct effect of the SAR models.

Table 4 presents own partial derivatives (direct effect), $Z_i/X_v i$, cross-partials derivatives (indirect effect), $Z_i/X_v j$, or spatial spillover effects in the case of spatial dependence. Of the household characteristics evaluated at the sample means in Table 4, farming experience had a positive and significant effect of 1% and a spatial spillover effect of about .3% for every additional year of farming experience, resulting in a total effect of 1.22%, ceteris paribus. Indirect effects are accumulated across all neighboring farmers, so the impact on individual farmers is likely smaller than the direct effects. In this particular case, we have observed that experienced smallholder farming households are more likely to change their preference for planting IBB seeds. This observation can also be applied to neighboring farmers. Farming experience is useful in the early stages of adoption when farmers are still testing the potential agricultural benefits of IBB. As bean farmers accumulate farming experience, they progressively change from traditional agricultural technologies to improved technologies on the basis of observed performance and learning by doing (Feder et al., 1985). We argue that the best way to transfer the advantages of new technologies is through face-to-face interaction, such as the classic example of an expert-novice relationship. We used farming experience and the management index as a proxy to transfer forms of tacit knowledge, such as the agronomic, nutritional benefits, input needed, yield, market prices, and demand for IBB. Howells (2002) argued that tacit knowledge concerns

TABLE 5 SDM probit model effect estimates for bush bean growers (M1)

	Direct effect			Indirect effect			Total effect		
Variables	Lower .05	Coefficient	Upper .95	Lower .05	Coefficient	Upper .95	Lower .05	Coefficient	Upper .95
Number of economic active males in HH	.0140	.0358	.0580	.0049	.0157	.0310	.0202	.0514	.0850
Number of children under 5 years old in HH	−.0694	−.0350	−.0010	−.0352	−.0155	−.0010	−.1024	−.0506	−.0020
Log (Household head age)	−.8809	.8359	2.5210	−.3629	.3713	1.2630	−1.2510	1.2070	3.8490
(Log (Household head age))^2	−.3714	−.1397	.0880	−.1847	−.0619	.0360	−.5518	−.2016	.1270
Wealth index	−.0951	.0780	.2560	−.0377	.0354	.1290	−.1328	.1134	.3720
Number of varieties cultivated	.0518	.0649	.0780	.0134	.0286	.0470	.0695	.0936	.1180
Farming experience (years)	.0046	.0082	.0120	.0014	.0036	.0070	.0064	.0118	.0180
Land labor ratio (m^2/person)	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000
Travel time to extension services >1 h	−.0088	.0198	.0500	−.0033	.0087	.0240	−.0126	.0285	.0710
Planting material from friends or relatives	2.2790	3.6010	5.2290	.7647	1.5210	2.3690	3.3140	5.1220	7.0990

with direct experience and is acquired through informal take- up of learned behaviors and procedures. We found that adoption by friends or relatives was positively correlated with the diffusion of IBB bush varieties. This finding broadly supports the theoretical work that links adoption of technology with social networks. Having male household members had a positive effect, with one additional male member increasing the adoption rate by 4%, and a positive indirect effect of 2%. Households are averse to adopting new varieties given the risk and uncertainty of their future performance. As a coping strategy to minimize the chances of food insecurity, households manage the risk of crop failure by cultivating multiple varieties. Growing an additional bean variety increases the probability of IBB adoption by 7% and a spatial spillover by 3%. The planting materials of relatives and friends had a positive direct and spatial spillover effect. Social interactions not only serve as a conduit for the dissemination of information, but also for the multiplication of IBB planting material.

Specification M2 aims to check the consistency of the estimated causal effect (Tables 2 and 6). We use four new covariates: household access to title land, household size, education level, and the management index or technical capacity. Due to the collinearity with the wealth index variables, we exclude the management index and education level variables in specification M1. The scalar parameter ρ in Table 2 measures the strength of spatial interdependence of the IBB propensity of adoption, with a value of zero indicating independence. Of the seven variables in Table 6, the effect of household management practices is statistically significant and positive. To capture the level of agricultural practices, the management index serves as a proxy of the inputs used by smallholder farming households in the current period X_t. When the management index increases from the lowest value of 0 to the highest value of 1, the probability of adoption will increase by 23%, the spillover effect will be around 17%, and the total effect will be 40%. As with any new technology, farmers who

TABLE 6 SAR and GLM probit model effect estimates for bush bean growers (M2)

	Direct effect			Indirect effect			Total effect			
	Lower .05	Coefficient	Upper .95	Lower .05	Coefficient	Upper .95	Lower .05	Coefficient	Upper .95	NSP
Household size	−.0185	.0015	.0220	−.0145	.0011	.0180	−.0335	.0026	.0390	.0000
Number of children under 5 years old in HH	−.1014	−.0457	.0100	−.0828	−.0337	.0060	−.1767	−.0793	.0160	−.0500
Log (Household head age)	−1.3881	.8601	3.1930	−1.0010	.6621	2.6190	−2.4401	1.5222	5.6960	.4500
(Log (Household head age))^2	−.4323	−.1289	.1670	−.3589	−.0987	.1230	−.7663	−.2277	.2960	−.0800
HH average years of schooling	−.0140	.0076	.0280	−.0099	.0056	.0220	−.0239	.0132	.0490	.0100
Share of land area with legal title	−.0002	.0005	.0010	−.0001	.0004	.0010	−.0004	.0009	.0020	.0000
Management index	.0726	.2295	.3860	.0427	.1671	.3110	.1236	.3966	.6590	.2700
Weighted plot slope	−.0052	−.0007	.0040	−.0040	−.0005	.0020	−.0090	−.0012	.0060	.0001
Travel time to extension services >1 h	−.0037	.0054	.0150	−.0028	.0040	.0120	−.0064	.0094	.0260	.0100

already use other agricultural inputs, such as fertilizers or manure, will use IBB varieties more frequently to increase agricultural productivity. Household education level, household size, and other variables were not significant.

Tables 5 and 7 summarize the SDM's marginal effects of bush bean growers. Of the nine explanatory variables included in specification M1 (Table 5), five are statistically significant at the 5% level for the estimates of the direct effect, which are "the number of economic active males in HH," "farming experience," "the number of bean varieties cultivated," "IBB planting material from friends or relatives," and "travel time to extension services." For specification M2 (Table 7), out of the seven included covariates, three variables—management index, the number of bean varieties, weighted plot slope, and access to extension services—are statistically significant at the 5% level for both the direct and the estimates of the indirect effects. The latter effect confirms the existence of spatial spillover effects or peer effects. Proximity to extension centers for smallholder farming households located >1 h away has a positive direct effect of 4% and a spatial spillover effect of 2%. This response is partially explained by the early delivery strategy of reaching out to the most vulnerable populations in remote rural areas, which have little to no access to agricultural inputs, are less technologically advanced, and are comparatively considered to be less wealthy farming households. Extension services can help guide farmers, particularly on the agricultural superiority of improved varieties such as iron-biofortified ones, strengthening farmers' knowledge and experience on agricultural best practices. Poorly functioning infrastructure can affect the profitability of the technologies used by farmers, and road networks (expansion and quality) and mobile services are among the most important infrastructure conditions. In general, transportation limitations tend to reduce competition between input suppliers and intermediaries. Empirical evidence suggests that the travel time between the farm gate and the market can be very long, partly due to underdeveloped road infrastructure (Raballand et al., 2010). Good transportation is associated with the dissemination of technology, better access to inputs, and higher producer prices (Ahmed & Hossain, 1990; Dorosh et al., 2009).

The management index also exerts a positive direct and indirect impact on the propensity of IBB adoption. This suggests that we would observe increased adoption rates on bean farmers that already use other agricultural practices like irrigation, terracing, fertilizer, pesticides,

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists
IAAE
WILEY

TABLE 7 SDM probit model effect estimates for bush bean growers (M2)

Variables	Direct effect Lower .05	Direct effect Coefficient	Direct effect Upper .95	Indirect effect Lower .05	Indirect effect Coefficient	Indirect effect Upper .95	Total effect Lower .05	Total effect Coefficient	Total effect Upper .95
Household size	−.0193	.0003	.0200	−.0131	.0000	.0130	−.0316	.0003	.0330
Number of children under 5 years old in HH	−.0952	−.0432	.0070	−.0693	−.0266	.0040	−.1593	−.0698	.0110
Log (Household head age)	−1.2900	.8683	3.0640	−.7704	.5786	2.3080	−2.0067	1.4469	5.1810
(Log (Household head age))^2	−.4201	−.1292	.1590	−.3108	−.0854	.0890	−.7110	−.2145	.2460
HH average years of schooling	−.0127	.0084	.0300	−.0082	.0052	.0200	−.0206	.0135	.0480
Share of land area with legal title	−.0003	.0004	.0010	−.0002	.0003	.0010	−.0006	.0007	.0020
Management index	.0945	.2560	.4000	.0364	.1618	.3230	.1467	.4179	.7010
Weighted plot slope	.0043	.0115	.0190	.0008	.0005	.0110	.0063	.0165	.0270
Travel time to extension services >1 h	.0029	.0388	.0750	.0014	.0247	.0580	.0049	.0635	.1280

manure, and/or compost. The indirect impact of management practices on nearby farmers is almost half of the direct impact. It can be seen that compared with other variables, the spatial spillover impact of the adoption rate is very large. Using the interaction between the management practice index and the number of bean varieties grown at the household level, we discovered the synergistic use of modern agricultural inputs.

We use the slope of the cultivated land as an indicator of soil quality. Plots' steepness positively affects the propensity of IBB adoption, with a positive direct and indirect impact of increasing IBB adoption. Empirical evidence in Rwanda shows that smallholder farming households that grew beans on steep terrains witness an increase in crop productivity as well as a decrease in soil erosion (Katungi et al., 2019). A potential explanation for this pattern might be the nitrogen-fixing ability of the common bean (*P. vulgaris*). Beans can obtain a part of the nitrogen they need from the atmosphere through symbiotic nitrogen fixation (Barbosa et al., 2018).

Figure E1 (see Appendix E) shows the point estimate of village-level random effects. The values of the point estimates change from one village to its neighbors, ranging from .2 to .8 with a higher prevalence of villages with negative point estimates. However, we can observe a few clusters of villages in the Eastern, Kigali, and Southern regions that have positive point estimates, which increase the likelihood of adoption and geographic spread of IBB bush varieties across these clusters of villages. As this analysis shows, random effects are a useful indicator of the degree of spatial heterogeneity of smallholder farming households in Rwanda.

3.3 | Climbing bean analyses

Scenario 1 for climbing bean adopters shows a different spatial pattern (Table 3). Contrary to IBB bush adopters, the propensity of adoption of IBB climbing varieties increases with household wealth and risk-taking households or households with less farming experience. In the SDM, the direct and indirect effects turned statistically significant at the 5% level (Table 9) for four covariates: household wealth, the number of bean varieties cultivated, years of farming experience, and IBB planting material received from friends or relatives. The largest total marginal effect was associated with IBB planting material from friends or relatives followed by the household wealth,

TABLE 8 SAR and GLM probit model effect estimates for climbing bean growers (M1)

Variables	Direct effect Lower .05	Coefficient	Upper .95	Indirect effect Lower .05	Coefficient	Upper .95	Total effect Lower .05	Coefficient	Upper .95	NSP
Number of economic active males in HH	−.0076	.0130	.0340	−.0033	.0061	.0170	−.0110	.0191	.0520	.0100
Number of children under 5 years old in HH	−.0366	−.0014	.0330	−.0188	−.0009	.0150	−.0550	−.0022	.0470	.0000
Log (Household head age)	−1.7880	−.1710	1.4900	−.8426	−.0855	.6800	−2.5790	−.2565	2.1010	−.1300
(Log (Household head age))^2	−.1752	.0433	.2600	−.0811	.0210	.1270	−.2585	.0643	.3730	.0400
Wealth Index	.0548	.2222	.3890	.0216	.1037	.2100	.0799	.3259	.5820	.2500
Number of varieties cultivated	.0361	.0493	.0610	.0106	.0232	.0370	.0518	.0725	.0930	.0500
Farming experience (years)	−.0142	−.0078	−.0020	−.0080	−.0037	−.0010	−.0215	−.0116	−.0030	−.0100
Land labor ratio (m^2/person)	−.0001	.0000	.0000	.0000	.0000	.0000	−.0001	.0000	.0000	.0000
Travel time to extension services >1 h	−.0052	.0019	.0090	−.0022	.0009	.0050	−.0074	.0028	.0140	.0000
Planting material from friends or relatives	1.5060	2.0900	2.6480	.4906	.9590	1.4270	2.3490	3.0490	3.7960	6.3600

which increased the probability of adoption by 25%, the number of bean varieties grown by the household, which increased the propensity of adoption by 5%. In response to the risks associated with crop failure and food insecurity, bean farmers grow more than one bean variety.

In scenario M2, four variables turned statistically significant at the 5% level: management practices, household size, household education level, and plot slope (Table 10). The size of the household has a positive effect on the propensity to adopt IBB, with a positive direct impact of increasing adoption by 2% for an additional member in the household. Larger households have the capacity to increase the labor availability required with the adoption of a new variety, such as IBB, while household education level had a direct impact of increasing the likelihood of adoption by 3%. Most notably, the results suggest that the average education level of household members (rather than the education level of the head of household) influences the adoption of new technology, and it is positively correlated with wealth. Farmers with higher levels of education are wealthier, therefore the education-adoption relationship may represent the income effect (Jolliffe, 2002). Also, as it was reported in the descriptive statistics, wealth may be correlated with the scale of operation, as adopters tend to manage more and larger plots. Analogous to bush bean growers, steep terrain can affect the adoption of IBB. In Rwanda, climbing bean production is more likely at higher elevations where smallholder farming households farm on steep slopes. Climbing beans is considered as a potential solution to increase agricultural productivity and soil sustainability (Katungi et al., 2019).

Tables 8 to 11 summarize the observed values of the estimates of the marginal effects for specifications M1 and M2 of the SAR and SDM models for climbing bean growers. Out of the nine covariates of the SDM model effect for specification M1 (Table 9), only four covariates are

TABLE 9 SDM probit model effect estimates for climbing bean growers (M1)

Variables	Direct effect Lower .05	Coefficient	Upper .95	Indirect effect Lower .05	Coefficient	Upper .95	Total effect Lower .05	Coefficient	Upper .95
Number of economic active males in HH	−.0126	.0101	.032	−.0052	.0042	.016	−.0181	.0144	.046
Number of children under 5 years old in HH	−.0356	.0017	.036	−.0144	.0007	.016	−.0478	.0024	.052
Log (Household head age)	−1.6920	−.0686	1.587	−.7542	−.0147	.729	−2.3270	−.0833	2.303
(Log (Household head age))^2	−.1862	.028	.243	−.0873	.0099	.105	−.2726	.0378	.34
Wealth Index	.0966	.2508	.414	.0223	.1062	.231	.1296	.357	.619
Number of varieties cultivated	.0368	.0507	.064	.0079	.0212	.039	.0494	.0719	.096
Farming experience (years)	−.0140	−.0083	−.0030	−.0071	−.0034	−.0010	−.0197	−.0116	−.0040
Land labor ratio (m^2/person)	−.0001	0	0	0	0	0	−.0001	0	0
Travel time to extension services >1 h	−.0228	.0046	.031	−.0088	.0022	.015	−.0310	.0068	.045
Planting material from friends or relatives	1.514	2.524	3.66	.4232	.9989	1.609	2.24	3.523	4.733

statistically significant at the 5% level: farming experience, the number of bean varieties cultivated, the wealth index, and IBB planting material from friends or relatives. The positive direct effect of the number of bean varieties cultivated and planting material from friends or relatives suggests that higher values of these variables for bean growing household i lead to an increase in the propensity of adoption of IBB climbing varieties. Farming experience shows that there is a negative direct impact, which indicates that household heads with less farming experience are more likely to adopt IBB climbing varieties. Contrary to IBB bush growers, novice climbing bean growers are more likely to change their seed use, which will have a positive spillover effect on neighboring farmers. This finding is consistent with the previous literature, that is, novice farmers are more inclined to adjust the level of input (Conley & Udry, 2010). The increase in agricultural experience reduces the tendency to respond to new information related to agricultural technology. This difference in the relationship between IBB adoption and farming experience between bush and climbing varieties might be related to the fact that climbing bean varieties are relatively newer than bush bean varieties (Katungi et al., 2019). Recent evidence shows that there is a significant inverted U relationship between the adoption of agricultural technology and agricultural experience (Ainembabazi & Mugisha, 2014). In a study investigating the determinants of the adoption of improved technology and production practices in Nepal, Kumar et al. (2020) reported that longer farming experience was negatively correlated with the adoption rate of agricultural technology. The socioeconomic characteristics of neighboring bean farmers, such as their household size and education level, have a positive spatial spillover effect on the adoption rate of IBB. The greater the magnitude of the estimated parameters of these covariates, the greater the tendency to adopt IBB climbing varieties. For specification M2 (Table 11), out of the seven included covariates, four variables—management index,

TABLE 10 SAR and GLM probit model effects estimates for climbing

	Direct effect			Indirect effect			Total effect			
	Lower .05	Coefficient	Upper .95	Lower .05	Coefficient	Upper .95	Lower .05	Coefficient	Upper .95	NSP
Household size	.0049	.0208	.0370	.0023	.0147	.0300	.0076	.0355	.0650	.0200
Number of children under 5 years old in HH	−.0454	.0018	.0480	−.0326	.0015	.0370	−.0770	.0033	.0830	.0000
Log (Household head age)	−1.3024	.6107	2.5070	−.8752	.4333	1.9360	−2.1882	1.0440	4.3230	.5300
(Log (Household head age))^2	−.3257	−.0770	.1720	−.2498	−.0545	.1180	−.5594	−.1314	.2890	−.0700
HH average years of schooling	.0135	.0280	.0440	.0064	.0198	.0360	.0221	.0478	.0770	.0300
Share of land area with legal title	−.0011	−.0004	.0000	−.0008	−.0003	.0000	−.0019	−.0007	.0010	.0000
Management Index	.0153	.1454	.2800	.0093	.1022	.2150	.0241	.2476	.4830	.1700
Weighted plot slope	−.0061	−.0028	.0000	−.0051	−.0020	.0000	−.0106	−.0048	.0000	−.0027
Travel time to extension services >1 h	−.0108	−.0023	.0060	−.0078	−.0015	.0040	−.0182	−.0038	.0110	.0000

the slope of farming plots, household size, and household average years of schooling—are statistically significant at the 5% level for both the direct and the estimates of the indirect effect. In contrast to IBB bush varieties, the last two covariates are not statistically significant.

The national adoption rate of IBB varieties was 28%. To better understand patterns of IBB adoption at the subnational level, Figure 1 contains a choropleth map of the prevalence rates of IBB adoption by bean types at the district level. From this map, we highlight two spatial patterns. First, from the choropleth map, it is clear that the rates of adoption for IBB bush varieties are higher in the Eastern region and gradually decreasing toward the Central, Southern, and Western regions. IBB climbing varieties, on the other hand, have higher rates of IBB adoption in the Western and Northern regions. IBB bush varieties are more likely to be adopted in the central and southern regions.

Figure E2 (see Appendix E) shows the point estimates of the village-level random effect of IBB climbing growers. The values of the point estimates range from -1 to 1 with a higher prevalence of villages with point estimates that range between -1 and 0. The spatial footprint of villages with positive point estimates is more frequent in the Southern, Western, Northern regions as well as the southern part of the Eastern region. Villages in these regions are more likely to adopt IBB climbing varieties. Figure E2 (see Appendix E) also illustrates the case of the distance-decay correlation across villages. In addition to within-village correlation, a spatial model assumes that the strength of spatial correlation between two villages declines as the distance between them increases, resulting in similar mean levels of outcomes among nearby villages and thus clusters of villages with similar outcomes.

4 | CONCLUSIONS

This article contributes to the literature on technology adoption in two ways. First, it provides a national and a subnational analysis on the intensity of adoption and adoption rates of IBB by type: bush and climbing. Second, the article examines, with the assistance of spatial econometrics techniques and theories of social interaction, and choice behavior, how household and farm level characteristics, as well as regional factors, influence smallholder farmers' decisions to grow IBB. We used a cross-sectional

TABLE 11 SDM probit model effect estimates for climbing bean growers (M2)

Variables	Direct effect Lower .05	Coefficient	Upper .95	Indirect effect Lower .05	Coefficient	Upper .95	Total effect Lower .05	Coefficient	Upper .95
Household size	.0040	.0216	.0390	.0023	.0143	.0300	.0069	.0360	.0660
Number of children under 5 years old in HH	−.0350	.0132	.0600	−.0241	.0088	.0440	−.0595	.0220	.1000
Log (Household head age)	−1.4887	.4314	2.3560	−.9581	.3192	1.8200	−2.3999	.7505	4.1490
(Log (Household head age))^2	−.3065	−.0530	.1990	−.2364	−.0394	.1270	−.5366	−.0925	.3260
HH average years of schooling	.0131	.0288	.0440	.0064	.0193	.0370	.0216	.0481	.0760
Share of land area with legal title	−.0010	−.0003	.0000	−.0007	−.0002	.0000	−.0016	−.0004	.0010
Management Index	.0118	.1479	.2940	.0062	.0995	.2260	.0194	.2474	.4950
Weighted plot slope	.0007	.0061	.0120	.0002	.0041	.0100	.0011	.0103	.0200
Travel time to extension services >1 h	−.0309	.0008	.0340	−.0208	.0009	.0240	−.0496	.0017	.0550

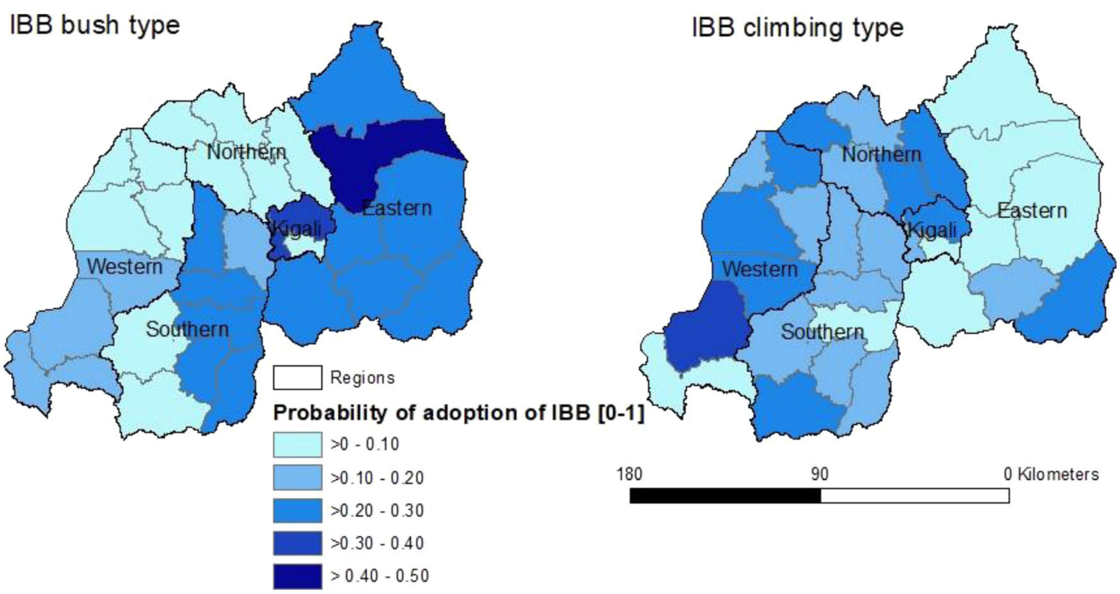

FIGURE 1 Choropleth map: prevalence rate of IBB adoption, by district

nationally representative survey of bean producing households on bean varieties grown in 2015 season B in Rwanda. We employed two SP specifications, SAR model, and SDM, to empirically assess the interdependence of farmers' decisions to adopt IBB. The robustness of our results was tested by setting a simple social grouping where smallholder farmers are nested within villages. This multilevel fixed model with random effect (at the village level) revealed spatial clustering across villages with similar outcomes by bean type.

The tabular analysis of the data shows that local bean varieties still dominate the area under bean cultivation, followed by improved and IBB varieties, respectively. Given that IBB varieties were only released 3–5 years prior to the time of the survey, 11% coverage figure indicates the intensity of adoption of IBB, suggesting early stages within a long-run S-shaped adoption curve. Our spatial econometric results indicate interdependence on farmers' decisions to adopt IBB. In addition to the directly targeted beneficiaries, the parameter ρ suggests that the biofortification program affected nonbeneficiaries as well. This finding indicates that (1) a bean growing farm household is more likely to grow IBB if the household is near other early IBB adopters who communicated on the nutritional and yield advantages of IBB technology, and (2) the tendency of households to grow IBB varies according to the characteristics of the neighboring farmers. A NSP model could not have measured this spatial association as an indicator of the interaction of farmers in a social network.

Structural factors are the main direct and indirect determinants for predicting the likelihood of adoption of IBB varieties. For IBB bush variety growers, these factors include the number of economically active male members in a household and farm management practices. In absolute terms, the largest total marginal effect is management practices. For IBB climbing variety growers, household size and education level had the highest direct and an indirect effect on the adoption of IBB. Common factors that influence the adoption of both climbing and bush IBB varieties included the number of years of farming experience and the number of varieties cultivated. Farming experience had a negative direct impact, as well as a negative spatial spillover on the household's propensity to adopt IBB climbing varieties. In contrast, years of farming experience had a positive direct impact on the adoption of bush IBB varieties and a positive spatial spillover. The second common factor that influenced the adoption of IBB varieties is the number of bean varieties cultivated. We observed a positive direct effect associated with the number of varieties cultivated, suggesting that a higher value of this variable leads to an increase in the propensity to adopt IBB varieties by the household. We considered the variable planting material sourced from friends or relatives of a smallholder farmer as a covariate. For growers of both bush and climbing IBB varieties, the coefficient of this covariate is positive and significant, which further supports the positive role of social interaction in technology diffusion.

Some general policy implications can be drawn from the initial above results. First, drafting differentiated geolocation strategies for bush and climbing beans based on the characteristics of farmers and farms may increase the adoption rate of the most vulnerable groups in rural areas. Second, given that education increases the propensity to adopt climbing IBB varieties, increasing training and extension on the nutritional and agronomic benefits of IBB might be an effective policy to stimulate the diffusion of this technology. Finally, technology-promotion programs that consider progressive farmers and strengthen social interactions and group activities among peer networks are expected to increase the spread of information and geographical diffusion of IBB varieties. Overall, in terms of policy implications, this study highlights the important role of social interactions as a cost- effective delivery strategy for diffusion of new technologies, such as IBB. In terms of methodological innovations, this study highlights the important role spatial econometric techniques can play in conducting program evaluations, especially regarding the impact of a program on unintended beneficiaries.

ACKNOWLEDGMENTS

This research was supported by CGIAR's Standing Panel on Impact Assessment (SPIA) under the Grant "Strengthening Impact Assessment in the CGIAR System (SIAC)" and HarvestPlus. HarvestPlus' principal donors are the UK Government; the Bill & Melinda Gates Foundation; the US Government's Feed the Future initiative; Global Affairs Canada; the European Commission; and donors to the CGIAR Research Program on Agriculture for Nutrition and Health (A4NH). HarvestPlus is also supported by the John D. and Catherine T. MacArthur Foundation and the Children's Investment Fund Foundation.

REFERENCES

Abdulai, A., Monnin, P., & Gerber, J. (2008). Joint estimation of information acquisition and adoption of new technologies under uncertainty. *Journal of International Development*, *20*(4), 437–451. https://doi.org/10.1002/jid.1422

Ahmed, R., & Hossain, M. (1990). Developmental impact of rural infrastructure in Bang*ladesh (Research report 93)*. International Food Policy Research Institute. Retrieved from https://ebrary.ifpri.org/digital/collection/p15738coll2/id/126676

Ainembabazi, J. H., & Mugisha, J. (2014). The role of farming experience on the adoption of agricultural technologies: Evidence from smallholder farmers in Uganda. *The Journal of Development Studies*, *50*(5), 666–679. https://doi.org/10.1080/00220388.2013.874556

Anselin, L. (1988). *Spatial econometrics: Methods and models*. Springer Science & Business Media.

Anselin, L., & Arribas-Bel, D. (2013). Spatial fixed effects and spatial dependence in a single cross-section. *Papers in Regional Science: The Journal of the Regional Science Association International*, *92*(1), 3–17. https://doi.org/10.1111/j.1435-5957.2012.00480.x

Anselin, L., & Rey, S. J. (2014). Modern spatial econometrics in practice: A guide to GeoDa. *GeoDaSpace and PySAL*: GeoDa Press LLC.

Asare-Marfo, D., Birol, E., Gonzalez, C., Moursi, M., Perez, S., Schwarz, J., & Zeller, M. (2013). *Prioritizing countries for biofortification interventions using country-level data (HarvestPlus*

Working paper 11). Retrieved from https://www.harvestplus.org/sites/default/files/working_paper_11_small.pdf

Asare-Marfo, D., Herrington, C., Alwang, J., Birachi, E., Birol, E., Diressie, M. T., Dusenge, L., Funes, J., Katungi, E., Labarta, R., LaRochelle, C., Katsvairo, L., Lividini, K., Lubowa, A., Moursi, M., Mulambu, J., Murekezi, A., Musoni, A., Nkundimana, J. d'A., … Zeller, M. (2016). *Assessing the adoption of high-iron bean varieties and their impact on iron intakes and other livelihood outcomes in Rwanda (43)*. Retrieved from http://ebrary.ifpri.org/cdm/ref/collection/p15738coll2/id/130809

Barbosa, N., Portilla, E., Buendia, H. F., Raatz, B., Beebe, S., & Rao, I. (2018). Genotypic differences in symbiotic nitrogen fixation ability and seed yield of climbing bean. *Plant and Soil*, *428*(1), 223–239. https://doi.org/10.1007/s11104-018-3665-y

Berti, P. R., Moursi, M., Kung'u, J. K., Tugirimana, P. L., Siekmans, K., Lubowa, A., & Boy, E. (2012). *Inadequate diet, but low iron deficiency anemia, in Rwandan women and children*. Unpublished project report, HarvestPlus.

Bivand, R., Sha, Z., Osland, L., & Thorsen, I. S. (2017). A comparison of estimation methods for multilevel models of spatially structured data. *Spatial Statistics*, *21*, 440–459. https://doi.org/10.1016/j.spasta.2017.01.002

Case, A. (1992). Neighborhood influence and technological change. *Regional Science and Urban Economics*, *22*(3), 491–508. https://doi.org/10.1016/0166-0462(92)90041-X

Comola, M., Inguaggiato, C., & Mendola, M. (2021). Learning about farming: Innovation and social networks in a resettled community in Brazil (Centro Studi Luca d'Agliano Development Studies Working Paper No. 468). Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3784592

Conley, T. G., & Udry, C. R. (2010). Learning about a new technology: Pineapple in Ghana. *American Economic Review*, *100*(1), 35–69. https://doi.org/10.1257/aer.100.1.35

Dong, G., & Harris, R. (2015). Spatial autoregressive models for geographically hierarchical data structures: Hierarchical spatial autoregressive models. *Geographical Analysis*, *47*(2), 173–191. https://doi.org/10.1111/gean.12049

Dorosh, P., Wang, H. G., You, L., & Schmidt, E. (2012). Road connectivity, population, and crop production in Sub-Saharan Africa. *Agricultural Economics (Amsterdam, Netherlands)*, *43*(1), 89–103. https://doi.org/10.1111/j.1574-0862.2011.00567.x

Durlauf, S. N., & Ioannides, Y. M. (2010). Social interactions. *Annual Review of Economics*, *2*(1), 451–478. https://doi.org/10.1146/annurev.economics.050708.143312

Elhorst, J. P. (2010). Applied spatial econometrics: Raising the bar. *Spatial Economic Analysis*, *5*(1), 9–28. https://doi.org/10.1080/17421770903541772

Ellison, G., & Fudenberg, D. (1993). Rules of thumb for social learning. *The Journal of Political Economy*, *101*(4), 612–643. https://doi.org/10.1086/261890

Fafchamps, M. (2010). Vulnerability, risk management, and agricultural development. *African Journal of Agricultural and Resource Economics*, *5*(1), 243–260.

Food /Agriculture Organization of the United Nations (FAO). (2000). *Manual on integrated soil management and conservation practices. Family Farming Knowledge Platform. Food/Agriculture Organization of the United Nations (FAO)*. ISBN: 92–5–304417–9. Retrived from https://www.fao.org/family-farming/detail/en/c/329712/

Food /Agriculture Organization of the United Nations (FAO). (2020). Food consumption. Retrieved from https://www.fao.org/faostat/en/#data/FBS

Feder, G., Just, R. E., & Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: A survey. *Economic Development and Cultural Change*, *33*(2), 255–298. https://doi.org/10.1086/451461

Foster, A. D., & Rosenzweig, M. R. (1995). Learning by doing and learning from others: Human capital and technical change in agriculture. *The Journal of Political Economy*, *103*(6), 1176–1209. https://doi.org/10.1086/601447

Foster, A. D., & Rosenzweig, M. R. (2010). Microeconomics of technology adoption. *Annual Review of Economics*, *2*, 395–424. https://doi.org/10.1146/annurev.economics.102308.124433

Gelman, A., Hwang, J., & Vehtari, A. (2014). Understanding predictive information criteria for Bayesian models. *Statistics and Computing*, *24*(6), 997–1016. https://doi.org/10.1007/s11222-013-9416-2

Ghadim, A. K. A., & Pannell, D. J. (1999). A conceptual framework of adoption of an agricultural innovation. *Agricultural Economics (Amsterdam, Netherlands)*, *21*(2), 145–154. https://doi.org/10.1016/S0169-5150(99)00023-7

Giné, X., & Yang, D. (2009). Insurance, credit, and technology adoption: Field experimental evidence from Malawi. *Journal of Development Economics*, *89*(1), 1–11. https://doi.org/10.1016/j.jdeveco.2008.09.007

Goldstein, H. (2003). *Multilevel statistical models. Third edition*. John Wiley & Sons.

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology*, *78*(6), 1360–1380. https://doi.org/10.1086/225469

Greene, W. H. (2012). *Econometric analysis* (7th ed.). Pearson.

Hall, B. H., & Khan, B. (2003). Adoption of new technology (WORKING PAPER 9730). Retrieved from https://www.nber.org/papers/w9730, https://doi.org/10.3386/w9730

Holloway, G., Shankar, B., & Rahmanb, S. (2002). Bayesian spatial probit estimation: A primer and an application to HYV rice adoption. *Agricultural Economics (Amsterdam, Netherlands)*, *27*(3), 383–402. https://doi.org/10.1111/j.1574-0862.2002.tb00127.x

Howells, J. R. L. (2002). Tacit knowledge, innovation and economic geography. *Urban Studies (Edinburgh, Scotland)*, *39*(5–6), 871–884. https://doi.org/10.1080/00420980220128354

Jamison, D. T., & Moock, P. R. (1984). Farmer education and farm efficiency in Nepal: The role of schooling, extension services, and cognitive skills. *World Development*, *12*(1), 67–86. https://doi.org/10.1016/0305-750X(84)90036-6

Jolliffe, D. (2002). Whose education matters in the determination of household income? Evidence from a developing country. *Economic Development and Cultural Change*, *50*(2), 287–312. https://doi.org/10.1086/322880

Katungi, E., Larochelle, C., Mugabo, J., & Buruchara, R. (2019). Climbing bean as a solution to increase productivity in land-constrained environments: Evidence from Rwanda. *Outlook on Agriculture*, *48*(1), 28–36. https://doi.org/10.1177/0030727018813698

Krishnan, P., & Patnam, M. (2014). Neighbors and extension agents in Ethiopia: Who matters more for technology adoption? *American Journal of Agricultural Economics*, *96*(1), 308–327. https://doi.org/10.1093/ajae/aat017

Kumar, A., Takeshima, H., Thapa, G., Adhikari, N., Saroj, S., Karkee, M., & Joshi, P. K. (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. https://doi.org/10.1016/j.landusepol.2020.104621

Lacombe, D. J., & LeSage, J. P. (2018). Use and interpretation of spatial autoregressive probit models. *The Annals of Regional Science*, *60*, 1–24. https://doi.org/10.1007/s00168-015-0705-x

Lee, L.-F., Liu, X., & Lin, X. (2010). Specification and estimation of social interaction models with network structures: Estimation of social network models. *The Econometrics Journal*, *13*(2), 145–176. https://doi.org/10.1111/j.1368-423X.2010.00310.x

LeSage, J. P., Kelley Pace, R., Lam, N., Campanella, R., & Liu, X. (2011). New Orleans business recovery in the aftermath of Hurricane Katrina: Business recovery in the aftermath of hurricane Katrina. *Journal of the Royal Statistical Society. Series A, (Statistics in Society)*, *174*(4), 1007–1027. https://doi.org/10.1111/j.1467-985X.2011.00712.x

LeSage, J., & Kelley Pace, R. (2009). Motivating and interpreting spatial econometrics models. In R. William & N. Balakrishnan (Ed.), *Schucany. Introduction to spatial econometrics* (pp. 1–354). Taylor & Francis.

LeSage, J., & Kelley Pace, R. (2014). The biggest myth in spatial econometrics. *Econometrics*, *2*(4), 217–249. https://doi.org/10.3390/econometrics2040217

Maertens, A., & Barrett, C. B. (2013). Measuring social networks' effects on agricultural technology adoption. *American Journal of Agricultural Economics*, *95*(2), 353–359.

Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *The Review of Economic Studies*, *60*(3), 531–542. https://doi.org/10.2307/2298123

Munshi, K. (2004). Social learning in a heterogeneous population: Technology diffusion in the Indian Green Revolution. *Journal of Development Economics*, *73*(1), 185–213. https://doi.org/10.1016/j.jdeveco.2003.03.003

Nourani, V. (2019). *Multi-object social learning and technology adoption in Ghana: Learning from friends and re-acting to acquaintances*. Department of Economics, Massachusetts Institute of Technology.

Petry, N., Boy, E., Wirth, J. P., & Hurrell, R. F. (2015). Review: The potential of the common bean (*Phaseolus vulgaris*) as a vehicle for iron biofortification. *Nutrients*, *7*(2), 1144–1173. https://doi.org/10.3390/nu7021144

Raballand, G., Macchi, P., & Petracco, C. (2010). *Rural road investment efficiency: Lessons from Burkina Faso, Cameroon, and Uganda* (ISBN-13: 978-0-8213-8214-1). World Bank. Retrieved from https://openknowledge.worldbank.org/bitstream/handle/10986/2425/536460PUB0Rura101Official0Use0Only1.pdf?sequence=1&isAllowed=y

Raftery, A. E., & Lewis, S. M. (1992). [Practical Markov chain Monte Carlo]: Comment: One Long Run with diagnostics: Implementation strategies for Markov chain Monte Carlo. *Statistical Science: A Review Journal of the Institute of Mathematical Statistics*, *7*(4), 493–497. https://doi.org/10.1214/ss/1177011143

Rue, H., Martino, S., & Chopin, N. (2009). Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. *Journal of the Royal Statistical Society. Series B, Statistical Methodology*, *71*(2), 319–392. https://doi.org/10.1111/j.1467-9868.2008.00700.x

Shiferaw, B., & Holden, S.. (2005). Assessing the economic and environmental impacts of conservation technologies. In B. Shiferaw, H. A. Freeman, & S. M. Swinton (Eds.), *Natural resource management in agriculture. Methods for assessing economic and environmental impacts* (pp. S269–S294). CABI Publishing.

Tessema, Y. M., Asafu-Adjaye, J., Kassie, M., & Mallawaarachchi, T. (2016). Do neighbours matter in technology adoption? The case of conservation tillage in northwest Ethiopia. *African Journal of Agricultural and Resource Economics*, *11*(3), 211–225. https://doi.org/10.22004/ag.econ.245940

Ulimwengu, J. M., Funes, J., Headey, D. D., & You, L. (2009). Paving the way for development: The impact of road infrastructure on agricultural production and household wealth in the Democratic Republic of Congo. Retrieved from https://ageconsearch.umn.edu/record/49292/

Ward, P. S., & Pede, V. O. (2015). Capturing social network effects in technology adoption: The spatial diffusion of hybrid rice in Bangladesh. *Australian Journal of Agricultural and Resource Economics*, *59*(2), 225–241. https://doi.org/10.1111/1467-8489.12058

Watanabe, S. (2013). A widely applicable Bayesian information criterion. *Journal of Machine Learning Research*, *14*, 867–897. https://dl.acm.org/doi/10.5555/2567709.2502609

Weir, S., & Knight, J. (2007). Production externalities of education: Evidence from rural ethiopia. *Journal of African Economies*, *16*(1), 134–165. https://doi.org/10.1093/jae/ejl026

Wilhelm, S., & Godinho de Matos, M. (2013). Estimating spatial probit models in R. *The R Journal*, *5*(1), 130–143. https://doi.org/10.32614/RJ-2013-013

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Funes, J., Sun, L., Sedano, F., Baiocchi, G., & Benson, T. (2022). Social interaction and geographic diffusion of iron-biofortified beans in Rwanda. *Agricultural Economics*, 1–26. https://doi.org/10.1111/agec.12722