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The Role of Social Interaction in the Adoption and Geographic Diffusion of an Agricultural Technology:

The Case of High Iron Bean (*Phaseolus Vulgaris*) in Rwanda

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Selected Paper prepared for presentation at the 2018 Agricultural & Applied Economics Association Annual Meeting, Washington, D.C., August 5-August 7

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Abstract

This study analyzes smallholder farmers' decisions to adopt high-iron beans in Rwanda using theories on social interactions and choice behavior. I approach this study by applying spatial econometric techniques to estimate neighborhood influence and to determine the factors driving the adoption of high-iron beans (HIB). To estimate the strength of social interactions and the robustness of the results, I use different spatial econometric techniques, including the Bayesian spatial autoregressive probit model and spatial Durbin model. I present results for both bush-bean growers and climbing-bean growers, using cross-sectional household survey data of bean varieties grown in season B in Rwanda. Season B sowing dates span from around January to March, followed by harvest activities from June to July. The results show that the adoption of HIB bush and climbing varieties exhibits positive spatial autocorrelation and spatial spillovers. This indicates that geographic diffusion of HIB seed occurs among neighboring farmers that exhibit interdependent decision-making patterns, as well as similar characteristics relative to the group. I compare the results to a standard probit model. Significant spatial spillovers in the results show that the use of standard probit models for this analysis would have generated biased and inefficient estimates. Some general policy implications can be drawn from the initial results. First, continuing to add market demand traits to the HIB varieties, such as drought resilience, stimulates the adoption of the improved bean varieties. These additional traits also have multiplier effects on neighboring bean farmers. Second, drafting a differentiated geographical targeting strategy for bush and climbing bean varieties as a function of farmer and farm characteristics increases HIB adoption rates. Third, strengthening partnerships with service providers, like NGOs, can stimulate the adoption of high-iron beans. Last, strengthening social interactions and group activities among peer networks increases the spread of information and geographical diffusion on HIB varieties.

Keywords: high-iron beans, Rwanda, spatial diffusion, neighborhood effect, spatial econometrics, social interaction

1. Introduction

Common bean (*Phaseolus vulgaris*) is the most important legume and one of the most important sources of protein for Rwandan families. Beans are staple food crops in Rwanda. Rwanda ranks number 1 out 81 countries suitable for investing in iron beans (HarvestPlus 2015). It provides up to 50 percent of daily iron needs. In 2012, the National Agricultural Research System of Rwanda, in collaboration with the International Center for Tropical Agriculture (CIAT), released the first high-iron bean (HIB) varieties to farmers in Rwanda. These biofortified varieties demonstrated micronutrient enrichment and better yield performance and have been enhanced to tolerate growth-reducing factors, like pests and diseases, and growth-limiting factors, such as droughts. However, little is known about key factors of adoption on the demand side and their potential impact on the income and welfare of the target population of smallholder bean farmers.

Understanding factors that drive HIB adoption among bean farmers is critical to help better design policies to increase food crop productivity in Rwanda. This paper analyzes farmers' participation in the HarvestPlus[1] biofortification program in Rwanda by examining factors on the demand side[2] and the role of peers. I draw upon theory from studies on the adoption of agricultural technology, social behavior, and spatial econometric methods. Most of the research literature on the adoption and impact of new agricultural technologies employs standard theories and modeling approaches, ignoring potential spatial association among economic agents – here, the farmers.

In this paper, I estimate and test for the presence of spatial association among economic agents (farmers) and any potential interactions with contextual factors. The spatial autoregression parameter in technology adoption studies contains important policy information (Case 1992). Mapping its geographic distribution can provide guidance to extension agents as to how specific initial investments in technology promotion will generate further geographic diffusion of a technology (Halloway et al. 2002). I implement spatial probit models for discrete-choice data using Bayesian modeling. The use of Bayesian modeling to estimate spatial processes was suggested first by Anselin (1988) and developed by LeSage (2009). These new methods produce

[1] HarvestPlus is a leader in the global effort to end hidden hunger caused by the lack of essential vitamins and minerals in the diet, such as vitamin A, zinc, and iron.

[2] On the supply side, we refer to HarvestPlus mechanisms of delivery and geolocation of agrodealers. A second paper looks closely into adoption patterns across eight seasons, combining spatial network analysis and spatial econometrics to explore the effect of proximity of farmers and the geolocation of suppliers by mechanisms of delivery.

useful measures of direct and spatial spillover impacts from changes in the explanatory variables (LeSage 2009). This study sets the stage for investigating the causal effect of adopting biofortified bean seeds by combining an impact evaluation framework and spatial econometric techniques. I then conduct two additional research studies: a study on crop yield estimation and a study on technical efficiency analysis. I dedicate separate papers to these studies.

The remainder of this paper is organized into four sections. Section 2 provides a brief literature review on definitions of adoption and provides a summary of the most cited characteristics of adoption and applied theoretical frameworks. Section 3 sets out the conceptual framework for the study and gives the general descriptive statistics for the variables used in our analysis. Section 4 analyzes the determinants of adoption and spillover effects for HIB in Rwanda. Section 5 provides general conclusions.

2. Related Research Literature: Definitions, Characteristics, and Theoretical Frameworks of Adoption

This section introduces formal definitions of adoption and diffusion of an agricultural innovation, synthetizes commonly cited characteristics and constraints that affect the adoption of such technology, and provides a short summary of the most commonly used theoretical frameworks on agricultural innovation.

Definitions of Adoption and Diffusion

Technology adoption is defined as the choice of a farmer to acquire and use an innovation. Many studies measure adoption of innovation by two variables: a discrete choice as to whether or not to utilize an innovation, and a continuous variable such as on the timing or extent of new technology utilization by individual farmers (Sunding and Zilberman 2001). In this study, I estimate, at national and province levels, the total area allocated to bean production with biofortified bean varieties and the number of bean farmers cultivating biofortified HIB seed in season B of 2015.

A recent stream of literature shows the importance of social networks, or peer-effects, as a mechanism for the spatial diffusion of technology, particularly so in developing economies (Beaman et al. 2015, Manski 1993). Here, I model social network through geometric distance. This is can be operationalized through geometric distance, trade flow, or other measure of interaction between economic agents. In spatial regression analysis, measures of spatial association include the spatial autoregressive parameter through different spatial weight structures, which are defined by the analysts. The spatial autoregressive parameter represents a way to model structed dependence between observations that arise peer effects or economic research (LeSage 2009). I provide further theoretical background on spatial econometrics in the conceptual framework section.

Established economic literature defines innovation diffusion as an aggregate measure of adoption and thereby analyzes the process through which the innovation penetrates markets and replaces traditional technologies (Sunding and Zilberman 2001). Measures of innovation diffusion include the percentage of the farming population that adopts new innovations and the share in total land on which innovations can be utilized. Namely, innovation diffusion is a process by which an innovation is communicated through certain channels over time among the members of a social system (Rogers 1995).

Commonly Cited Characteristics and Constraints that Affect the Adoption and Diffusion of Innovation Agricultural Technology

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 and Barrett 2013). Empirical studies have shown the effect of social networks on facilitating the adoption of new agricultural technologies in developing countries. Foster and Rosenweig (1995) find that farmers with neighbors who have more farming experience have higher profits than those without such neighbors. Krishnan and Patnam (2014) find evidence that social learning was more persistent than learning from extension services for the adoption of new seed varieties and fertilizer in Ethiopia. Conley and Udry (2010) examine how learning from the experience of others and the flow of information depend on the structure of social networks when there is no access to agricultural extension services. Ward and Pede (2015) find that neighbor effects are a significant determinant of hybrid rice use. They use two specifications to model the endogenous effect of being neighbors—one based on membership in the same village, and the other based on geographical distance.

Other factors driving adoption include farm size, access to credit, land tenure, human capital, infrastructure, and wealth. Farm size was one of the first factors explored in the empirical literature on adoption. Farm size can have different effects on the rate of adoption 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 surrogate for many potentially important factors, such as access to credit, capacity to bear risk, access to scarce inputs, wealth, and access to information. Many studies have examined the role of access to credit and appropriate financial instruments as a constraint in farmers' adoption decisions (seeds, fertilizers, and pesticides). According to theoretical and empirical research studies, access to capital through either accumulated savings or capital markets is necessary to finance the adoption of many new agricultural technologies, especially for smallholder farmers. Simtowe and Zeller (2009) find higher hybrid maize adoption among households with access to credit in Malawi. Chirwa (2005) finds that close to 60 percent of sampled households in Malawi do not use hybrid maize varieties, but that adoption increases with income, education, and farm size. Croppenstedt, Demeke, and Meschi (2003), estimating a model of fertilizer use in Ethiopia, find that household cash resources are generally insufficient to cover fertilizer purchases.

There are two methods commonly used in the literature to quantify the role of credit constraints. One is to ask farmers the primary reason they do not adopt a particular technology to determine if the reasons might be correlated with either wealth or income.[3] The second method is to look for income, scale, and insurance effects (Foster and Rosenzweig 2009).

A number of empirical and descriptive studies have also considered the effects of land tenure arrangements[4] and the proportion of farms rented on the adoption of new agricultural technology, such as high-yielding varieties. Findings suggest that land tenure favors adoption of technology. The form of tenure (e.g., renters, sharecroppers, landowners) may affect the adoption decisions and diffusion rates. In Ethiopia, Shiferaw and Holden (1998) did not find any significance in the tenure regime for a plot explaining the adoption of land conservation practices on that plot. In Rwanda land ownership favored HIB adoption.

Poor-functioning infrastructure affects the profitability of technology adopted by farmers, and road networks (extension and quality) and mobile services rank among the most important infrastructural conditions. In general, transportation problems tend to reduce competition among input suppliers and middlemen. Empirical evidence shows that travel times between the farm gate and market are high due in part to underdeveloped road infrastructure (Jack 2013). Good

[3] The problem with this method arises if the returns to adoption of technology vary by farm scale.
[4] It can be considered a good measure of wealth.

transportation is associated with a diffusion of technology, better access to inputs, and better prices (Ahmed and Hossain 1990).

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. The last mechanism has been the principal focus of economists (Foster and 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 seems to be implied. Jamison and Mook (1984) test the effect of schooling and extension contacts on the adoption and diffusion of agriculture in Nepal. They find that schooling influences adoptive behavior, but that household income mediates the adoption decision. Weir and Knight (2000) 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. Gine 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.

The local and regional geographical setting within villages—including geographical variables such as rainfall, soil type, ethnic groups, slope, farmer management practices in a village, population density, road density, and market access—might vary and, therefore, have an impact on yield differentials across farmers adopting the same technology.

Theoretical Frameworks

Economic studies have commonly distinguished between models of technology adoption and models of technology diffusion (path of aggregate demand). The most accepted theoretical analytical frameworks for investigating adoption of technology include (1) economic constraints (probit model), (2) adopter perceptions (probit model), (3) innovation-diffusion (epidemic models) (Adesina and Zinnah 1993; Geroski 2000), and (4) spatial diffusion through social network (spatial econometric models).

The last theoretical framework is perhaps the most recent to propagate in the literature (Conley and Udry 2010). Seminal work by Manski (2000) identifies three sources of social influence: (1) endogenous effects, (2) exogenous network effects, and (3) correlated effects. Most examples in agricultural technology diffusion place an emphasis on modeling the endogenous effects. Common spatial econometric methods include the spatial error model and the spatial lag model (Halloway et al. 2002; Ward and Pede 2014). I extend these methods by modeling the endogenous and exogenous network effects using the spatial Durbin model.

This paper explores the spatial structure of HIB adopters. Biofortification is relatively a new market in Rwanda and localization is a key factor for understanding the diffusion of biofortified seeds. I assume that the decision of a household bean grower to adopt biofortified seed is spatially correlated. Therefore, the bean farmer's decision to adopt HIB seed depends not only on his/her characteristics and on his/her farm's features, but it is correlated with the decisions of neighboring bean farmers and their characteristics. Therefore, the household bean grower that is close to an HIB adopter has a higher probability of being an HIB adopter as well, 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 in average in agreement with their social group. Whether diffusion of biofortified seed is geographically determined, the spillover effects will determine a strong spatial relationship, i.e., similar farms will tend to be localized in the same geographical area. Therefore, within a region, it is possible to find similar: economic structures, wealth and management practices levels, and family structures.

Economic constraint modeling is probably the most extensively used theoretical approach in the literature for examining the adoption of agricultural innovation. Research studies commonly apply the farmer's decision-making model, which is well documented by Feder *et al.* (1982). Using this model, it is assumed that farmers' decisions result from the maximization of an expected utility against constraints such as land, access to credit, market access, infrastructure, etc. Farmer profits are defined as a function of the farmer's choice of crops to cultivate (traditional vs. modern plus other crops) and technology level *b* at time *t*. Therefore, a farmer's income is a function of land allocated to different crops, which can, consequently, be explained by the production function of each crop: yields, inputs (amount and prices), and other associated costs of production. To address the decision over time, Feder *et al.* (1982) and Feder and O'Mara (1981) suggest empirical models that factor in perceived parameters of the production function. These parameters could be updated from learning processes that incorporate prior perception and recent information about yields, input uses, prices, etc., of farmers in any region using Bayesian modeling of learning rules to update farmers' perceptions. Other variables considered in structural equations include extension services and human capital. Other dynamic variables include optimal timing of technology adoption, learning by using, and learning by doing, which demand a wealth of data, such as a panel survey, for analysis.

Another less cited theoretical approach is a framework based on farmers' perceptions of technology characteristics. Agricultural technology attributes (e.g., yields, drought resistance, pest resistance) and consumers' subjective perceptions (e.g., taste) can be significant in explaining decisions to use a particular technology. Recent research applied to agriculture includes seminal papers by Adesina and Zinnah (1993) and Adesina and Forson (1995). These studies assume farmers' adoption decisions are based on the non-observable underlying utility function, which ranks preference by $U(M_{ji}, A_{ji})$, where M is a vector of farm and farmer-specific attributes of the adopter, and A is a vector of the attributes associated with the technology. Adesina and Zinnah examine farmer technology adoption conditioned to farmer perceptions of technology-specific characteristics of mangrove swamp rice varieties in Sierra Leone. Adesina and Forson explore farmers' perceptions of modern sorghum and rice varietal technologies in Burkina Faso and Guinea. Joshi and Pandey (2005) estimate a model of modern rice varieties in Nepal. Their findings suggest that farmers' perceptions of varietal characteristics, such as pest resistance or drought tolerance, were important in determining technology choices in the areas where current adoption rates are high.

An associated theory to adoption of new technology is the product price treadmill, in which farmers continually seek to improve their incomes by adopting new agricultural innovations. Early adopters make profits for a short time because of their lower unit production costs. As more farmers adopt the technology, production goes up, prices go down, and profits are no longer possible, even with lower production costs. Average farmers are forced by lower product prices to adopt the technology and lower their production costs to remain in the market. The laggards who do not adopt agricultural innovations are lost in the price squeeze and leave room for their more successful neighbors to expand (Sunding and Zilberman 2001).

3. Conceptual Framework and Data

Conceptual Framework

Discrete-choice models 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 farmers' decisions on whether or not to adopt biofortified seed.

A bean farmer's expected profit from adopting a biofortified seed, instead of a local seed or other improved variety, depends on different sets of variables. These variables include prices on inputs and output; 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 seed availability in the market.

I start with a basic latent regression model as shown in equation (1). I 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 utilities achieved (Greene 2000). I model the difference between benefit and cost as an unobserved variable, $y^* = \pi_{1i} - \pi_{0i}$, which represents the difference in utility where π_{1i} represents the utility associated with variety 1, and π_{0i} the utility from other varieties, such that

$$y^* = x'\beta + \varepsilon \tag{1}$$

I assume that ε has a mean of zero. My only observation of the data generation process is

$$\begin{aligned} y &= 1 \text{ if } y^* > 0 \\ y &= 0 \text{ if } y^* < 0. \end{aligned} \tag{2}$$

The farmer either did adopt ($Y = 1$) or did not adopt ($Y = 0$) biofortified beans in season B of 2015. I believe that a set of intrinsic factors such as farmer characteristics, plot characteristics, and environmental factors gathered in a vector x, explain farmers' decisions, so that:

$$\begin{aligned} \text{Prob}\,(Y = 1|x) &= \text{F}(x, \beta) \\ \text{Prob}(Y = 0|x) &= 1 - \text{F}(x, \beta)\ . \end{aligned} \tag{3}$$

The set of parameters β reflects the impact of changes in x on the probability. For instance, the marginal effect of household head age on the probability of adoption of HIBs may be a factor of interest.

Normally, the estimation of $\text{P}(X) = \text{Pr}(\text{C} = 1 \mid X)$ is done by means of a probit or logit model. However, when there are spatial effects, conventional models calculated by maximum likelihood are not adequate. By construction, the errors of a spatial logit model are heteroscedastic, and estimates based on the hypothesis of homoscedasticity in the presence of heteroscedastic errors are inconsistent (Greene 2000; Wooldridge 2001). Therefore, spatial probit models are used to calculate the probability, P(X)=Pr(D = 1 | X), or propensity, of being an HIB grower for each observation.

Spatial econometrics

To the basic probit model, I add a spatial structure to explore the spatial clustering of the variable of interest, adoption of biofortified beans. I follow two motivations, theoretical and statistical. Theoretically, bean farmers in small villages may imitate each other, leading to spatial dependence or peer effects. Statistically, the spatial nature of the cross-sectional dataset (household with GPS locations) requires spatial econometrics modeling to account for spatial autocorrelation and spatial heterogeneity (Anselin 1998). Spatial dependence can emerge from unobservable latent variables that are spatially correlated (Anselin 1988; LeSage 2009; Anselin and Rey 2014).

In contrast to the standard probit and logit model, where y^*h represents the latent unobservable utility that depends not only on observable determinants of household h represented by X, spatial probit modeling also depends on other household neighbors latent variables y^*h_j.

I use spatial econometric theory on Bayesian spatial probit modeling presented by LeSage and Pace (2009). I test the robustness of the results by using two spatial model structures: the Bayesian spatial autoregressive (SAR) and the Bayesian spatial Durbin model (SDM). Below, I present the data generation process and a brief motivation for each model.

The motivation for the SAR model (or spatial lag model) is the potential dependence on the social influence of households within villages (LeSage and Pace 2014), as SAR is useful to estimate the social autocorrelation in social networks. From the listing database, villages, each with between 100 and 170 households, are small enough for households to know each other, but large and close enough to measure a degree of social interactions. For this study, I use a subsample that includes 10 percent of each village. Thus, a household's social network consists of households within their home village that interact with one or more of their neighbors.

In greater detail, the SAR model, as suggested by LeSage (2009), is

$$y_h = \rho W y + X\beta + \varepsilon,\ \varepsilon \sim N(0, \sigma^2 I_n)\ , \tag{4}$$

for $y = (y_1, \ldots, y_n)'$ with some matrix of covariates X ($n \times k$) associated with the parameter vector β (k x 1). The matrix W (n x n), called the spatial weight matrix, captures the dependence structure between neighboring farmers. Wy is a linear combination of neighboring households. The scalar

ρ, the dependence parameter, is assumed to be (ρ) < 1. The k + 1-model parameters to be estimated are the parameter vector β and the scalar ρ.

The data generating process for y is

$$y = (I_n - \rho W)^{-1} X\beta + (I_n - \rho W)^{-1} \varepsilon$$
$$\varepsilon \sim N(0, I_n) \,. \qquad (5)$$

I employ a variation of the SAR model in our analysis—the SDM. This model allows variables from neighboring regions contained in the matrix X to exert an influence on the propensity of HIB adoption on household i. This is accomplished by entering an average of the explanatory variables from neighboring regions, created using the matrix product WX (LeSage 2008).

LeSage and Pace (2009, p. 32) provides the data generation process of the SDM as

$$y = \rho Wy + \alpha\iota + X\beta + WX\theta + \varepsilon;\ \varepsilon \sim N(0_{nx1}, \sigma^2 I_n) \,. \qquad (7)$$

The spatial lag latent dependent variable Wy involves the N x N spatial weight matrix W that contains elements consisting of either one or zero. All elements of the matrix W that are not associated with neighboring observations take values of zero. The scalar parameter ρ measures the strength of dependence, with a value of zero indicating independence. A nonspatial probit model emerges when $\rho = 0$.

Average marginal effect

In spatial models, a change in some explanatory variable x_i for observation i will not only affect the observations y_i directly (direct impact), but also affect neighboring observations y_j (indirect impact). These impacts potentially also include feedback loops from observation i to observation j and back to i (LeSage 2009; Lacombe and LeSage 2015). The scalar summary measure of indirect effects cumulates the spatial spillovers falling on all other observations, but the magnitude of impact will be greatest for nearby neighbors.

LeSage et al. (2011) construct a matrix version of the own partial and cross partial derivatives, where d(.) represents the $n \times 1$ vector on the diagonal of a diagonal matrix D(.), where the nondiagonal elements are zeros. By construction, D(.) is symmetric. The $n \times 1$ vector $d(f(n))$ contains the probability density function (pdf) evaluated at the predictions for each observation and associated $n \times n$ diagonal matrix $D(f(n))$, which has $d(f(n))$ on the diagonal. Using the matrix of own partial and cross partial derivatives, LeSage et al. (2011) show that an $n \times 1$ vector of total effects can be written as:

$$\frac{\partial \Pr(y=1)}{\partial x'_{\mathrm{v}}} \iota_\eta = \left[D\left(\left(f(\eta)\right)\iota_\eta + \rho D\left(f(\eta)\right) W \iota_\eta + \rho^2 D(\left(f(\eta)\right) W^2 \iota_\eta + \cdots \right] \beta_{\mathrm{v}}$$
$$= \left[D\left(\left(f(\eta)\right)\iota_\eta + \rho D\left(f(\eta)\right)\iota_\eta + \rho^2 D(\left(f(\eta)\right)\iota_\eta + \cdots \right] \beta_{\mathrm{v}}$$
$$= \left(D\left(\left(f(\eta)\right)\iota_\eta\right)(1-\rho)^{-1} \beta_{\mathrm{v}}$$
$$= \left(d\left(f(\eta)\right)\right)\iota_\eta)(1-\rho)^{-1} \beta_{\mathrm{v}} . \tag{8}$$

As a scalar summary measure of average total effect, LeSage et al. (2011) use an average of the vector of total effect,

$$n^{-1}(d\left(f(\eta)\right)' \iota_\eta)(1-\rho)^{-1} \beta_{\mathrm{v}} . \tag{9}$$

The average direct effect as proposed by LeSage et al. (2011) is

$$\frac{1}{n} tr\left(\frac{\partial \Pr(y=1)}{\partial x'_{\mathrm{v}}}\right)$$
$$= \left[tr(D\left(f(\eta)\right)) + \rho tr(D\left(f(\eta)\right) W) + \rho^2 tr(D\left(f(\eta)\right) W^2) + \cdots \right] \frac{\beta_{\mathrm{v}}}{n} . \tag{10}$$

For the average indirect effect, they propose using the difference between the average total effect and the average direct effect.

I used the nomenclature M1 and M2 for the two specifications used for each of the spatial probit models (SAR and SDM). Specification M1 aims to test how household characteristics such as wealth, household composition, HIB consumption, and years of farming experience play a role on HIB adoption. In addition, it explores the role of number of varieties used to manage risk of food insecurity due to crop failure caused by the prevalence of drought. Specification M2, on the other hand, looks at the importance of household technical capacity measured through the management index in connection to education level and household size. M2 drops the wealth index.

Data and Descriptive Statistics

<u>Data</u>

The basic data to conduct this research comes from an impact assessment study conducted in Rwanda in season B of 2015. The main aim of the survey is to investigate adoption of HIB varieties among Rwandan bean farmers. Data collection was split into two parts (two-stage sampling): 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,[5] out which 93 percent were bean growers. The sampling

[5] The country has approximately 14,000 villages.

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 8 out of 12 to run all statistical analyses. These modules include information on household roster, plot characteristics, bean production, bean varietal traits, HIB adoption history, household assets, and housing characteristics.

Descriptive Statistics

National statistics based on survey design

Annual food crop production in Rwanda follows the bimodal distribution of rainfall that divides crop cultivation into two major seasons: A and B.[6] We analyze adoption of HIBs for season B in 2015. At national level, 214,130 hectares were cultivated for bean production, of which 58 percent were allocated to bush and 42 percent to climbing varieties.

Local bean varieties still dominate bean production in Rwanda with the highest share of cultivated area at 68 percent, followed by improved and HIB varieties, at 21 and 11 percent, respectively. The latter figure indicates the intensity of adoption of biofortified beans. HIB bush varieties had a higher intensity of adoption than HIB climbing varieties, at 12 and 10 percent adoption rates, respectively. Of the total subpopulation of bean growers, 24 percent adopted HIBs.

About 80 percent of the area under bean cultivation comprised plots cultivated with either local, improved, or HIB varieties, and the other 20 percent were composed of mixed varieties (bush and climbing varieties). Plots with pure local varieties dominated, with 55 percent composed of bush and climbing (33 and 22 percent, respectively). The second-largest share was allocated to pure plots of improved varieties at about 16 percent, of which 8 percent were bush varieties, and 8 percent climbing. About 8 percent were plots cultivated with either bush or climbing HIB varieties, at 5 and 3 percent, respectively.

There are ten HIB varieties disseminated throughout Rwanda, out of which two are HIB bush varieties: RWR2245 and RWR2154. The former had an intensity of adoption of 11 percent of the total land area cultivated with bush bean varieties (157,416 hectares), while the later represented less than 1 percent. The remaining eight varieties are climbing beans with an intensity of

[6] Season A's sowing dates range from September to October, followed by harvest activities from January to March. Season B's sowing dates span from around January to March, followed by harvest activities from June to July.

adoption of 10 percent of the total land area cultivated with climbing beans (114,568 hectares). MAC42 was the most popular climbing bean variety, with almost 5 percent, followed by RWV3316 (~2 percent) and RWV1129 (1 percent). The other five varieties were cultivated in less than 1 percent of the area under bean cultivation.

At the subnational level, the spatial pattern of bean cultivation changes by variety. Bush bean varieties were mostly cultivated in the Eastern, Southern, and Western provinces, in descending order. The intensity of adoption of HIB bush varieties mirrors the natural geographic concentration of bush bean varieties, measured by cultivated area, in the Eastern (61 percent), Southern (32 percent), and Western (3 percent) Provinces. However, the intensity of adoption of HIB climbing varieties does not follow the natural geographic clustering of climbing bean area (Northern, Western, Southern, Eastern, and Kigali); rather, it follows the geographic concentration of bush bean cultivation. Cultivation of HIB climbing varieties is concentrated, in descending order, in the Eastern (58 percent), Southern (17 percent), Northern (16 percent), and Western (9 percent) Provinces, and in Kigali (<1 percent). These figures may be partially explained by biofortified bean availability in the market.

Seventy-one percent of the cultivated land area was owned under a title, 14 percent had no title, and 12 percent was rented land. In descending order, bean utilization breaks down as grain used for home consumption (60 percent), sale in local markets (17 percent), crop given away (6 percent), and seed for next season (6 percent). 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. The management practices included in the management index (see Appendix) are factors that fall within two categories: growth-factor limiting (e.g., access to irrigation and use of fertilizer, manure, and compost) and growth-reducing factors (e.g., use of pesticides). Households in the city of Kigali were on average wealthier than their counterparts from other regions. The second-wealthiest rural households were located on the Western Province, followed by households in the Northern Province. Less wealthy households were in the Southern and Eastern provinces.

Survey statistics

Table 1 reports descriptive statistics by adoption status and significance level of the most important characteristics of the 1,394 interviewed bean grower households in 2,516 plots and

3,017 subplots. Of these households, 36 percent cultivated only bush beans, 44 percent cultivated only climbing beans and 20 percent cultivated both bush and climbing beans.

Some of the listed variables are used in later analyses related to crop yield estimation and technical efficiency. I believe bush and climbing bean adopters come from two different data generating processes, so they are treated separately.

In Rwanda, more than 80 percent of the economically active population (EAP) are involved in agriculture. In this study, on average, households with a higher membership of the EAP have higher adoption of HIB, supporting the relevance of labor in the decision to adopt. The average household family size is statistically significant between adopters and non-adopters, suggesting the need to meet food demand. The average education level of adopters is statistically significant, a hint that interaction among family members influences adoption of new technology and is positively correlated with wealth. 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 biofortified seeds) to minimize the risk of food insecurity associated with crop failure or poor crop yield performance of a specific bean variety. As a proxy of household economic well-being and technical capacity, we use the wealth index and management index, respectively (see Appendix). Adopters were wealthier, more technical in their crop management practices, and experienced higher yields.

Table 1. Characteristics of adopters and non-adopters of high-iron beans (HIB) in Rwanda

Variables	**Non-adopters**	**HIB adopters**	**t-test**
Household characteristics			
Number of women 12 - 49 years old	2.03	2.22	0.00
Number of individuals 0-19 <= >= 65 years old	2.77	2.92	0.12
Number of people per household	4.80	5.14	0.01
Dependency ratio (children)	1.39	1.43	0.51
Number of individual per household - Economic active population [18-65]	2.68	2.93	0.00
Female household head (proportion of households)	0.27	0.26	0.66
Number of male members per households	2.22	2.54	0.00
Age of household head (years)	46.77	46.83	0.94
Level of education (average number of years in education per household)	2.82	3.46	0.00
Wealth Index	0.42	0.47	0.00
Years of farming experience	8.10	7.13	0.07
Farm characteristics and management practices			
Number of crops	1.78	1.87	0.08
Number of plots	2.97	3.34	0.00
Number of varieties	2.44	4.34	0.00
Percentage rented in land	13.97	11.06	0.08
Percentage own title	70.24	73.45	0.18
Percentage no title	13.17	14.07	0.63
Percentage share cropping	1.81	0.86	0.08
Total farm land (m)	2369.91	3092.79	0.00
Management index	0.39	0.45	0.00
Weighted plot slope (percent)	12.87	12.25	0.19
Land labor ratio (m^2/person)	998.82	1153.23	0.08
Walking distance in time from home to plot (minutes)	15.45	15.36	0.94
Land terraced (proportion of households)	0.22	0.26	0.13
Plot irrigated (proportion of households)	0.06	0.09	0.08
Hired labor (proportion of households)	0.35	0.49	0.00
Applied fertilizers (proportion of households)	0.20	0.26	0.03
Applied manure (proportion of households)	0.77	0.86	0.00
Applied compost (proportion of households)	0.59	0.66	0.02
Applied pesticide (proportion of households)	0.09	0.10	0.56
Bean area m2 (proportion of households)	1545.58	1927.93	0.00
Bean consumption (proportion of households)	0.06	0.09	0.00
Weighted average yield (kg/ha)	850.18	870.44	0.54
Access to credit (proportion of households)	0.21	0.20	0.54
Geography			
Region 1 (proportion of households)	0.02	0.02	0.81
Region 2 (proportion of households)	0.27	0.28	0.80
Region 3 (proportion of households)	0.26	0.16	0.00
Region 4 (proportion of households)	0.21	0.20	0.54
Travel time 50k (minutes)	248.80	254.65	0.54
DEM (meters)	1734.27	1658.07	0.00
Drought index	-0.03	-0.03	0.70
Number of observations	962.00	432.00	

Source: Authors' calculations.

4. Spatial Econometric Analysis

Results and Discussion: Adoption Model Estimates (non-spatial probit [NSP] vs. spatial probit [SP] models)

The coefficient estimates (posterior means, standard deviations, and Bayesian p-levels) for the two specifications (M1 and M2) for two spatial models (SAR and SDM) and a non-spatial probit model are shown in Tables 2 and 3, while tables 4 to 11 show the average marginal effects estimates. Tables 4 to 11 are the basis for inference regarding the effect of changes in the various independent variables on the probabilities that bean farmers will adopt HIBs and on the spatial spillover effect on neighboring bean farmers.

Tables 2 and 3 both have 7 columns; each column consists of parameter estimates and standards errors. I estimated two scenarios. For each scenario, I use a standard probit model and two spatial probit models. I describe and compare the average marginal effects for each model. There are three common covariates in both specifications: number of children in the household, age of household head, and accessibility to technical services. The specification M1 aims to test how household characteristics such as wealth, household composition, and years of farming experience play a role in HIB adoption. In addition, the M1 scenario explores the role of the number of 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. M2 does not include the wealth index because of its positive correlation with the management index and education level.

Bush bean analyses

Table 2 shows the signs of scenario 1 (M1) and scenario 2 (M2) on bush bean varieties. I observe that the signs of some covariates are consistent in the spatial probit models and non-spatial probit model. Years of farming experience, the number of varieties cultivated, management index, and the number of male members in the household have a positive influence on the propensity of adoption of biofortified HIB bush seed, while the number of children in the household, household age, and the drought index have a negative influence. Five of these covariates—namely number of children under five, household head age, wealth index, and the drought index have different signs in the non-spatial. In M1 and M2, four spatially-lagged independent variables—namely W-number of males in the household (HH), W-number of varieties cultivated, W-farming experience, and W-drought index—have positive parameters in terms of HIB adoption, while W-management index, W-wealth index, W-level of education, and W-travel time to technical services, had a negative indirect effect on household *i*. This indicates that household *i* propensity of HIB adoption is affected by neighbors' characteristics. However, the magnitude and signs of the average marginal effect of each variety is discussed in greater detail with the summary measures of direct, indirect, and total impacts below.

Tables 4–7 show the marginal effect outputs for the non-spatial and spatial probit models for bush bean growers. Tables 8–11 show the marginal effect estimate outputs for climbing bean growers. Tables 4, 6, 8, and 10 each have 11 columns. The first column lists all 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 percent) and upper (95 percent) bounds confident intervals for the SAR spatial probit model. The last column corresponds to the marginal effect of the standard non-spatial probit model, which is equivalent to the direct effect of the SAR models.

Spatial probit models, such as SAR and SDM, allowed us to disentangle the total marginal effect into direct and indirect impacts. 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. These effects are referred to as spatial spillovers. The estimated spatial autocorrelation coefficient on the lagged dependent variable ρ for the spatial Durbin model suggests spatial autocorrelation, which means the SDM specification, helps to estimate less bias estimates on the regression's parameters.

In general, the SAR model's indirect effects are smaller than the direct effects. The SAR model's direct impacts were nearly equal to the direct effects of the NS probit model's direct impacts. The SP and NSP models reported the same magnitude and signs on the average marginal effect for two covariates: age of household head and farming experience. Below, I provide a discussion of the average marginal effect for the SAR models.

Table 4 presents own partial derivatives (direct effect), $\frac{\partial Z_i}{\partial X_v i}$, and cross-partials derivatives (indirect effect), $\frac{\partial Z_i}{\partial X_v j}$, or spatial spillover effects in the case of spatial dependence. In the case of spatial spillover, changes of household bean grower *i*'s explanatory variable affect all *n-1* other household bean growers. It represents the spatial spillovers falling on neighboring bean farmers as well as neighbors to these bean farmers, declining for higher order neighbors. Of the household characteristics for HIB bush variety adopters (table 4) evaluated at the sample means, farming experience [+] had a positive and significant effect of 1 percent and a spatial spillover effect of about 1 percent for every additional year of farming experience for a total effect of 2 percent, ceteris paribus. Indirect effects are cumulated over all neighboring farmers, so the impact on individual neighboring farmers is likely smaller than the direct effects. I believe farming experience is useful in early stages of adoption, when farmers are still testing the potential agricultural and nutritional benefits of HIB. Male members of households had a positive effect, as every additional male member increases the adoption rate by 6 percent, and a positive indirect effect of 18 percent. Households are averse to adopting new varieties given the risk and uncertainty of seed performance. As a coping strategy to minimize the chances of food insecurity, households manage risk of crop failure by cultivating multiple varieties. The adoption of an additional seed variety increases the probability of adoption by 8 percent, and a spatial spillover of 2 percent. The age of household head shows a negative propensity of adoption decreasing by 1 percent with each additional year of the household head's age and a spatial spillover of 1 percent.

Specification M2 aims to check the consistency of the estimated casual effect (Table 6). I use four new covariates: household access to title land (+), household size (+), education level (-), and management index or technical capacity (+). The management index and education level variables were precluded in specification M1 because of collinearity with the wealth index variable. The scalar parameter ρ measures the strength of dependence, with a value of zero indicating independence. The magnitude of ρ varies from 0.20 to 0.23, suggesting significant positive spatial autocorrelation in bean farmers' decisions regarding adoption of biofortified seeds. In other words, there is a global social multiplier in the system that indirectly affect non-beneficiaries. The largest total marginal effect is associated with household management practices, increasing the probability of adoption by 23 percent, and a spillover effect of around 18 percent, for a total effect of 41 percent. I believe biofortified seeds would be more frequently used by farmers that already use other agricultural inputs, such as fertilizers or manure, to increase farm productivity. Household education level and size were not significant.

Tables 5, 7, 9, and 11 each have ten columns. Tables 5 and 7 summarize the SDM's marginal effects of bush bean growers, and tables 9 and 11 summarize the SDM's marginal effects of climbing bean growers. In the data from the Durbin model for bush varieties, specification M1, (table 5), out of the nine included explanatory variables, five variables have 95 percent non-zero confidence intervals for the direct effects estimates. These direct-effect variables include male members of households (+), age of household head (-), farming experience (+), number of varieties (+), and the drought index. None of the indirect-effect of these variables turned significant. For specification M2 (table 7), out of the seven included covariates, two variables—management index [+] and access to technical services [+]—have 95 percent non-zero confidence intervals for the direct and the indirect effects estimates. The latter effect confirms the presence of spatial spillovers or peer effects. Proximity to extension centers has a positive direct effect of 3 percent and a spatial spillover effect of 2 percent, which seems consistent with the notion of accessibility of farmers to agricultural extension agents. Extension services can help guide farmers, particularly on the nutritional benefits and potential agricultural superiority of biofortified seeds, strengthening farmers' knowledge and experience on agricultural best practices. This also confirms HarvestPlus' targeting strategy to reach farmers in remote rural areas with some accessibility to technical services. The management index also exerts a positive direct and indirect impact on the propensity of HIB adoption, suggesting that we would observe increased adoption rates on bean farmers that already use other agricultural practices like irrigation, terracing, fertilizer, pesticides, manure, and/or compost. The indirect impact from management practices in nearby farmers is almost half the magnitude of the direct impact, suggesting a moderate spatial spillover impact in adoption rates.

Climbing bean analyses

Scenario 1 for climbing bean adopters shows a different spatial pattern (Tables 3 and 8). Four variables, all of them significant, shift sign from what we saw in the bush bean analyses: household head age (+), farming experience (-), and wealth index (+). Contrary to HIB bush adopters, the probability of adoption of HIB climbing varieties increases with (1) household wealth, (2) household head's age, (3) less farming experience. In the SDM, the direct and direct effects turned significant (Table 9) for three covariates: wealth index, farming experience, and number of varieties cultivated. The direct impact of household head age was positively significant, suggesting that household head's age will have an impact on the adoption rates of

HIB climbing varieties. The indirect impact of household head age was not significant, suggesting no spatial spillover effect. The largest total marginal effect was associated with wealth, which increased the probability of adoption by 35 percent, followed by the number of bean varieties, which increased the propensity of adoption by 6 percent. To cope with the risk associated with crop failure and food insecurity, bean farmers cultivate more than a single seed variety.

In scenario M2, five variables turned significant in the climbing bean analyses: management practices [+], household size [+], education level [+], the lag effect of household size [-], and the lag effect of share of land area with legal title [-] (tables 3 and 10). Household size increases the propensity of adoption, with a positive direct impact of increasing adoption by 2 percent for an additional member in the household. Larger households have the capacity to increase the labor availability required during biofortified seed adoption, while household education level had a direct impact of increasing the probability of adoption by 3 percent. The average education level of household members influences the adoption of new technology and is positively correlated with wealth. Farmers that are more educated are wealthier, and thus the education–adoption relationship may represent an income effect. 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.

Tables 9 and 11 summarize the observed values of the marginal effects estimates for specifications M1 and M2 of the SDM model for climbing bean growers, respectively. The model effect for specification M1, out of the nine covariates, just four covariates have 95 percent non-zero confidence intervals: age of household head (+), wealth (+), farming experience (-) and number of varieties (+). The indirect effects were significant only for the last three covariates. The positive direct effect of the age of the head of household, the number of varieties cultivated, and wealth suggest that higher values of these variables in household bean grower *i* lead to an increase in the propensity of adoption of HIB climbing bean varieties. Farming experience indicates a negative direct effect suggesting that younger household heads are more likely to adopt HIB climbing bean varieties; contrary to bush bean growers that tend to be older. Socioeconomic characteristics of neighboring bean farmers like household size, level of education, and wealth exert positive spatial spillovers on HIB adoption rates. Higher magnitude of the estimated parameters of these covariates increases the propensity of the adoption HIB climbing varieties. The years of farming experience influenced a negative spatial spillover in adoption rates.

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

Variables	M1-SAR	M1-SDM	M2-SAR	M2-SDM	M1-NSP	M2-NSP
Constant	-0.81572**	-1.17391	-0.51253*	0.78210	-1.968***	-1.55069***
	(0.35296)	(1.19649)	0.32405	(0.90437)	(0.354)	(0.32519)
Household size			0.01185	0.009712		0.07791**
			(0.03391)	(0.03469)		(0.02929)
Number of males in HH	0.21631***	0.23359***			0.01356	
	(0.05486)	(0.05869)			(0.05272)	
Number of children under 5 years old in HH	-0.16029*	-0.16432*	-0.170998*	-0.161985*	-0.04198	0.004776
	(0.09006)	(0.09546)	(0.09465)	(0.09972)	(0.08728)	(0.09188)
Household head age	-0.02168***	-0.02202***	-0.00885*	-0.008201.	0.01081.	0.001304
	(0.00609)	(0.00617)	(0.00472)	(0.00508)	(0.00559)	(0.00433)
Level education			0.01565	0.02612		0.09499**
			(0.03923)	(0.03973)		(0.03145)
Wealth Index	-0.09221	-0.24848			1.323**	
	(0.49237)	(0.51944)			(0.436)	
Number of varieties cultivated	0.29603***	0.32415***			0.2234***	
	(0.03855)	(0.04073)			(0.03491)	
Farming experience (years)	0.03544***	0.03543***	0.035433***		-0.02923*	
	(0.00936)	(0.00971)			(0.0135)	
Share of land area with legal title			0.00185	0.0018		-0.00139
			(0.00149)	(0.00149)		(0.00139)
Management Index			0.79928**	0.93065**		0.56302*
			(0.30208)	(0.33322)		(0.27954)
Land labor ratio (m²/person)	-0.00003	-0.00003			-0.00006	
	(0.00004)	(0.00004)			(0.00007)	
Drought Index	-0.46051	-3.63509***			0.9041*	
	(0.38383)	(1.12227)			0.4427	
Travel time to technical services	-0.00597	0.09232*	0.01636**	0.09089*		-0.01103
	(0.02127)	(0.04858)	(0.01955)	(0.04336)		(0.02046)
W-Household size				0.09867		
				(0.11104)		
W-Number of males in HH		0.55657*				
		(0.24626)				
W-Number of children under 5 years old in HH		-0.33682		-0.36675		
		(0.31857)		(0.34834)		
W-Household head age		-0.00192		-0.01589		
		(0.02181)		(0.01738)		
W-Level education				-0.245636*		
				(0.12754)		
W-Wealth Index		-2.92459.				
		(2.05790)				
W-Number of varieties cultivated		0.33484*				
		(0.15554)				
W-Farming experience (years)		0.02429				
		(0.04729)				
W-Share of land area with legal title				0.00639*		
				(0.00452)		
W-Management Index				-0.94216.		
				(0.61986)		
W-land labor ratio (m2/person)		-0.00011				
		(0.00012)				
W-Drought Index		3.85099**				
		(1.34548)				
W-Travel time to technical services		-0.151315**		-0.10999*	-0.01993	
		(0.06041)		(0.04957)	(0.02132)	
Rho	0.19818*	0.04872	0.23237*	0.331361***		
	(0.08256)	(0.18939)	(0.07321)	(0.10705)		
Log likehood	-252.1125	-82.57425	-295.6187	-124.851	-255.6513	-294.3198

Note: HH: household. Significance level: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1

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

Variables	M1-SAR	M1-SDM	M2-SAR	M2-SDM	M1-NSP	M2-NSP
Constant	-1.86674***	-1.51653.	-1.46376***	-0.87035	-1.968***	-1.55069***
	(0.35973)	(1.152379)	(0.32794)	0.7763	(0.354)	(0.32519)
Household size			0.08051**	0.08974***		0.07791**
			(0.02949)	(0.0307)		(0.02929)
Number of males in HH	0.01811	0.01807			0.01356	
	(0.05187)	(0.05378)			(0.05272)	
Number of children under 5 years old in HH	-0.05454	-0.03698	0.01500	0.01235	-0.04198	0.00477
	(0.08930)	(0.09334)	(0.09197)	(0.09974)	(0.08728)	(0.09188)
Household head age	0.01025*	0.01091*	0.00212	0.00119	0.01081.	0.00130
	(0.00553)	(0.00608)	(0.00452)	(0.00455)	(0.00559)	(0.00433)
Level education			0.09592***	0.08917**		0.09499**
			(0.03113)	(0.03404)		(0.03145)
Wealth Index	1.36328***	1.39819***			1.323**	
	(0.44804)	(0.47311)			(0.436)	
Number of varieties cultivated	0.22404***	0.23357***			0.2234***	
	0.03614	(0.04064)			(0.03491)	
Farming experience (years)	-0.02887**	-0.02897***			-0.02923*	
	(0.01348)	(0.01224)			(0.0135)	
Share of land area with legal title			-0.00115	-0.00082		-0.00139
			(0.00148)	(0.00151)		(0.00138)
Management Index			0.47941*	0.44496.		0.56302*
			(0.26203)	(0.30707)		(0.27954)
Land labor ratio (m²/person)	-0.00001	-0.00003			-0.00005	
	(0.00006)	(0.00006)			(0.00006)	
Drought Index	0.767825*	1.15167*			0.9041*	
	(0.40540)	(0.61263)			(0.4427)	
Travel time to technical services	-0.014924	0.04347	-0.00606**	0.00503	-0.01993	-0.01103
	(0.02004)	(0.04426)	(0.01840)	(0.04883)	(0.02132)	(0.02046)
W-Household size				-0.15346*		
				(0.09027)		
W-Number of males in HH		0.02385				
		(0.21662)				
W-Number of children under 5 years old in HH		-0.32431		0.04314		
		(0.32765)		(0.30145)		
W-Household head age		0.00718		0.00944		
		(0.02085)		(0.01385)		
W-Level education				-0.00339		
				(0.08878)		
W-Wealth Index		-0.31861				
		(1.41665)				
W-Number of varieties cultivated		-0.14159.				
		(0.09749)				
W-Farming experience (years)		-0.01405				
		(0.03007)				
W-Share of land area with legal title				-0.00989**		
				(0.00398)		
W-Management Index				1.17544*		
				(0.66840)		
W-land labor ratio (m2/person)		0.00016		-0.01922		
		(0.00016)		(0.05092)		
W-Drought Index		-0.65531				
		(0.91909)				
W-Travel time to technical services		-0.0696.				
		(0.04982)				
Rho	0.25992***	0.32164***	0.26648***	0.32403**		
	(0.07319)	(0.10805)	(0.07055)	(0.11681)		
Log likehood	-301.446	-84.38166	-327.0876	-113.56446	-300.1071	-327.1027

Note: HH: household. Significance level: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

Table 4. SAR and GLM probit model effects estimates for bush bean growers (M1)

Variables	Direct effect			Indirect effect			Total effect			
	Lower 0.05	Coefficient	Upper 0.95	Lower 0.05	Coefficient	Upper 0.95	Lower 0.05	Coefficient	Upper 0.95	NSP
Number of males in HH	0.03001	0.05920	0.08625	0.00200	0.01486	0.03401	0.03527	0.07406	0.11331	0.06815
Number of children under 5 years old in HH	-0.08912	-0.04380	0.00436	-0.03213	-0.01098	0.00196	-0.11624	-0.05478	0.00549	-0.04894
Household head age	-0.00902	-0.00593	-0.00256	-0.00335	-0.00149	-0.00022	-0.01158	-0.00742	-0.00330	-0.00683
Wealth Index	-0.29081	-0.02547	0.24062	-0.07627	-0.00549	0.06984	-0.35645	-0.03096	0.29162	-0.02274
Number of varieties cultivated	0.06245	0.08098	0.09848	0.00273	0.02039	0.03920	0.07452	0.10137	0.12816	0.09663
Farming experience (years)	0.00484	0.00969	0.01442	0.00037	0.00243	0.00542	0.00631	0.01212	0.01858	0.01140
land labor ratio (m2/person)	-0.00003	-0.00001	0.00001	-0.00001	0.00000	0.00000	-0.00003	-0.00001	0.00002	-0.00002
Drought Index	-0.34142	-0.12580	0.06604	-0.10693	-0.03061	0.01952	-0.42391	-0.15641	0.08792	-0.18009
Travel time to technical services	-0.01278	-0.00162	0.01009	-0.00426	-0.00044	0.00271	-0.01678	-0.00206	0.01242	0.00032

Note: HH: household.

Source: Authors’ calculations.

Table 5. SDM probit model effects estimates for bush bean growers (M1)

Variables	Direct effect			Indirect effect			Total effect		
	Lower 0.05	Coefficient	Upper 0.95	Lower 0.05	Coefficient	Upper 0.95	Lower 0.05	Coefficient	Upper 0.95
Number of males in HH	0.02979	0.06027	0.08953	-0.01541	0.00434	0.02936	0.03295	0.06462	0.10182
Number of children under 5 years old in HH	-0.09450	-0.04738	0.00026	-0.02978	-0.00337	0.01528	-0.10934	-0.05075	0.00022
Household head age	-0.00885	-0.00551	-0.00239	-0.00281	-0.00039	0.00147	-0.00981	-0.00589	-0.00253
Wealth Index	-0.30620	-0.07083	0.17810	-0.07768	-0.00645	0.04166	-0.34222	-0.07728	0.19289
Number of varieties cultivated	0.06244	0.08344	0.10464	-0.02087	0.00634	0.04131	0.06033	0.08978	0.12932
Farming experience (years)	0.00385	0.00878	0.01413	-0.00231	0.00064	0.00442	0.00364	0.00941	0.01566
land labor ratio (m2/person)	-0.00003	-0.00001	0.00001	-0.00001	0.00000	0.00000	-0.00003	-0.00001	0.00001
Drought Index	-1.48404	-0.92288	-0.38192	-0.49777	-0.07035	0.22421	-1.72737	-0.99323	-0.38131
Travel time to technical services	-0.00150	0.02335	0.04716	-0.00654	0.00188	0.01428	-0.00147	0.02523	0.05399

Note: HH: household.

Source: Authors’ calculations.

Table 6. SAR and GLM probit model effects estimates for bush bean growers (M2)

Variables	Direct effect			Indirect effect			Total effect			NSP
	Lower 0.05	Coefficient	Upper 0.95	Lower 0.05	Coefficient	Upper 0.95	Lower 0.05	Coefficient	Upper 0.95	
Household size	-0.01721	0.00378	0.02550	-0.00599	0.00110	0.00936	-0.02247	0.00487	0.03392	0.00407
Number of children under 5 years old in HH	-0.11571	-0.05483	0.00255	-0.04271	-0.01683	0.00054	-0.15730	-0.07166	0.00325	-0.05641
Household head age	-0.00591	-0.00284	0.00010	-0.00230	-0.00087	0.00003	-0.00783	-0.00371	0.00013	-0.00275
Level education	-0.01958	0.00501	0.03036	-0.00649	0.00146	0.00993	-0.02585	0.00647	0.03980	0.00514
Share of land area with legal title	-0.00037	0.00059	0.00149	-0.00010	0.00018	0.00050	-0.00047	0.00077	0.00192	0.00057
Management Index	0.07072	0.25611	0.43169	0.01281	0.07852	0.17764	0.09218	0.33463	0.58097	0.28030
Travel time to technical services	-0.00738	0.00525	0.01749	-0.00195	0.00158	0.00610	-0.00927	0.00683	0.02237	0.00689

Note: HH: household.

Source: Authors' calculations.

Table 7. SDM probit model effects for bush bean farmers (M2)

Variables	Direct effect			Indirect effect			Total effect		
	Lower 0.05	Coefficient	Upper 0.95	Lower 0.05	Coefficient	Upper 0.95	Lower 0.05	Coefficient	Upper 0.95
Household size	-0.01818	0.00294	0.02508	-0.00946	0.00155	0.01383	-0.02619	0.00449	0.03737
Number of children under 5 years old in HH	-0.11285	-0.04960	0.00611	-0.07070	-0.02521	0.00490	-0.16880	-0.07481	0.00826
Household head age	-0.00568	-0.00251	0.00050	-0.00362	-0.00127	0.00027	-0.00849	-0.00378	0.00074
Level education	-0.01617	0.00804	0.03172	-0.00860	0.00440	0.01992	-0.02396	0.01243	0.04942
Share of land area with legal title	-0.00039	0.00055	0.00144	-0.00020	0.00029	0.00098	-0.00056	0.00084	0.00222
Management Index	0.08685	0.28518	0.47856	0.02194	0.14881	0.36064	0.12342	0.43399	0.78788
Travel time to technical services	0.00105	0.02786	0.05427	0.00012	0.01445	0.03593	0.00144	0.04231	0.08191

Note: HH: household.

Source: Authors' calculations.

Table 8. SAR and GLM probit model effects estimates for climbing farmers (M1)

Variables	Direct effect			Indirect effect			Total effect			NSP
	Lower 0.05	Coefficient	Upper 0.95	Lower 0.05	Coefficient	Upper 0.95	Lower 0.05	Coefficient	Upper 0.95	
Number of males in HH	-0.02371	0.00508	0.03409	-0.01397	0.00321	0.02280	-0.03613	0.00829	0.05470	0.00400
Number of children under 5 years old in HH	-0.06614	-0.01494	0.03156	-0.04515	-0.00937	0.01830	-0.10568	-0.02431	0.05203	-0.01239
Household head age	-0.00024	0.00287	0.00582	-0.00014	0.00164	0.00398	-0.00039	0.00450	0.00937	0.00319
Wealth Index	0.09272	0.35012	0.58815	0.04433	0.20383	0.42322	0.14954	0.55395	0.96674	0.39045
Number of varieties cultivated	0.03964	0.05828	0.07719	0.01204	0.03355	0.05775	0.06071	0.09183	0.12472	0.06597
Farming experience (years)	-0.01653	-0.00858	-0.00118	-0.01144	-0.00489	-0.00062	-0.02641	-0.01348	-0.00205	-0.00863
land labor ratio (m2/person)	-0.00004	0.00000	0.00003	-0.00002	0.00000	0.00002	-0.00006	0.00000	0.00004	-0.00002
Drought Index	-0.05342	0.17099	0.38395	-0.02505	0.09978	0.26056	-0.07973	0.27077	0.61683	0.26690
Travel time to technical services	-0.01379	-0.00297	0.00713	-0.00934	-0.00176	0.00426	-0.02294	-0.00473	0.01113	-0.00588

Note: HH: household.

Source: Authors' calculations.

Table 9. SDM probit model effects for climbing bean farmers (M1)

Variables	Direct effect			Indirect effect			Total effect		
	Lower 0.05	Coefficient	Upper 0.95	Lower 0.05	Coefficient	Upper 0.95	Lower 0.05	Coefficient	Upper 0.95
Number of males in HH	-0.02342	0.00443	0.03433	-0.01632	0.00189	0.02071	-0.04003	0.00632	0.05084
Number of children under 5 years old in HH	-0.05457	-0.00448	0.04395	-0.03308	-0.00265	0.02554	-0.08251	-0.00713	0.06343
Household head age	0.00020	0.00314	0.00628	-0.00006	0.00163	0.00446	0.00023	0.00477	0.01009
Wealth Index	0.12852	0.35286	0.59088	0.00929	0.18365	0.44415	0.17293	0.53651	0.99710
Number of varieties cultivated	0.04213	0.06057	0.07960	0.00262	0.03083	0.06478	0.05768	0.09139	0.13308
Farming experience (years)	-0.01513	-0.00757	-0.00133	-0.01082	-0.00391	-0.00007	-0.02405	-0.01148	-0.00176
land labor ratio (m2/person)	-0.00004	-0.00001	0.00002	-0.00003	-0.00001	0.00001	-0.00007	-0.00002	0.00003
Drought Index	-0.40165	0.14038	0.68581	-0.23528	0.07154	0.42747	-0.63524	0.21192	1.02886
Travel time to technical services	-0.01961	0.00600	0.03149	-0.01186	0.00314	0.01889	-0.03059	0.00915	0.04955

Note: HH: household.

Source: Authors' calculations.

Table 10. SAR probit model effects estimates for climbing bean growers (M2)

Variables	Direct effect			Indirect effect			Total effect			NSP
	Lower 0.05	Coefficient	Upper 0.95	Lower 0.05	Coefficient	Upper 0.95	Lower 0.05	Coefficient	Upper 0.95	
Household size	0.00423	0.02227	0.03945	-0.05651	-0.01947	0.01744	-0.04080	0.00280	0.04478	0.02405
Number of children under 5 years old in HH	-0.04112	0.01281	0.07103	-0.09301	0.02159	0.13846	-0.10575	0.03440	0.17332	0.00147
Household head age	-0.00163	0.00103	0.00362	-0.00400	0.00144	0.00686	-0.00437	0.00246	0.00896	0.00040
Level education	0.00897	0.02921	0.05013	-0.04605	-0.00818	0.03138	-0.02057	0.02103	0.06749	0.02932
Share of land area with legal title	-0.00111	-0.00030	0.00051	-0.00372	-0.00191	-0.00010	-0.00436	-0.00221	-0.00015	-0.00043
Management Index	-0.00745	0.16666	0.34087	-0.07224	0.23308	0.51817	0.06199	0.39974	0.74889	0.17378
Travel time to technical services	-0.03231	0.01624	0.06837	-0.07578	-0.02242	0.02421	-0.02082	-0.00618	0.00810	-0.00340

Note: HH: household.

Source: Authors' calculations.

Table 11. SDM probit model effects for climbing bean farmers (M2)

Variables	Direct effect			Indirect effect			Total effect		
	Lower 0.05	Coefficient	Upper 0.95	Lower 0.05	Coefficient	Upper 0.95	Lower 0.05	Coefficient	Upper 0.95
Household size	0.00802	0.02483	0.04260	0.00179	0.01302	0.03201	0.01214	0.03784	0.06913
Number of children under 5 years old in HH	-0.04813	0.00334	0.05768	-0.03011	0.00161	0.03637	-0.07459	0.00495	0.08975
Household head age	-0.00212	0.00032	0.00264	-0.00114	0.00020	0.00184	-0.00320	0.00051	0.00429
Level education	0.00638	0.02465	0.04442	0.00116	0.01287	0.03149	0.00903	0.03752	0.07013
Share of land area with legal title	-0.00103	-0.00022	0.00063	-0.00064	-0.00011	0.00039	-0.00160	-0.00034	0.00098
Management Index	-0.05326	0.12270	0.28744	-0.02441	0.06422	0.21088	-0.07578	0.18692	0.46021
Travel time to technical services	-0.02642	0.00138	0.02895	-0.01462	0.00074	0.01821	-0.03954	0.00212	0.04370

Note: HH: household.

Source: Authors' calculations.

5. Conclusions

The tabular analyses indicate that local bean varieties still dominate the area under bean cultivation at 68 percent, followed by improved and HIB varieties, at 21 and 11 percent of area cultivated, respectively. The latter indicates the intensity of adoption of biofortified beans, suggesting early stages within a long-run S-shaped curve of HIB adoption.

This paper uses two spatial probit specifications (SAR and SDM) to empirically assess the interdependence of farmers' decisions to adopt high iron beans. The empirical results suggest significant positive spatial autocorrelation in bean farmers' decisions to adopt biofortified seeds, as well as spatial spillovers or exogenous effects on bean farmers' decisions to adopt HIB varieties. This finding indicates that (1) farmer *i* is more likely to adopt biofortified seeds if she/he is near other HIB earlier adopters and (2) the propensity of farmer *i* to adopt HIB varieties varies with characteristics of his/her neighboring farmers. A non-spatial probit model would not measure spatial association as an indicator of interaction of farmers in a social network.

The number of years of farming experience and the number of varieties cultivated are common factors that influence the adoption of HIB varieties for bush bean growers and climbing bean growers. The results show that farming experience has a negative direct impact, as well as a negative spatial spillover on farmer's *i* propensity to adopt HIB climbing varieties. In contrast, with respect to the adoption of HIB bush varieties, years of farming experience have a positive direct impact and a positive spatial spillover. This suggests that neigboring farmers *j* with more years of farming experience exert a positive influence on farmer *i* to adopt HIB bush varieties. Farming experience is associated with early stages of adoption, when farmers learn about yield potential and nutritional benefits.

The second common factor that influences adoption of HIB is the number of varieties cultivated. We observe 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 HIB varieties in farmer *i*. Spatial spillover of the number of varieties used in neighboring farmers is positive and significant. Due to household yield uncertainty in securing food sufficiency in a household and as a coping strategy to secure food security, households manage the risk of crop failure by cultivating multiple varieties.

Bush Varieties

Structural factors are the main direct and indirect determinants for predicting the likelihood of adoption of HIB bush varieties. These factors include the number of males in a household, management practices, and the age of the household head. Other factors include proximity to extension centers. In absolute terms, the largest total marginal effect is associated with the drought index followed by management practices. We believe biofortified seeds would be more frequently used by farmers that already use other agricultural inputs, such as fertilizers or manure, irrigation, and pesticides to increase their farms' productivity.

Climbing Varieties

Structural and non-structural factors like household size, average education level, household head age, and wealth exert positive direct and spatial spillover effect in the adoption of HIB climbing bean varieties. The largest total positive marginal effect was associated with wealth, followed by households' location relative to areas vulnerable to drought. I use a drought index as an indicator for estimating the impact of drought as a climate-induced hazard in Rwanda agricultural production.

Some general policy implications can be drawn from the initial results. First, continually adding market-demand traits, such as resilience to drought, diseases and pests, as well as high yielding varieties, stimulates adoption of HIB. These additional traits also have multiplier effects on neighboring bean farmers. For example, if farmers save seeds for next season, they may give/sell them to other neighboring farmers. Second, drafting a differentiated geographical targeting strategy for bush and climbing bean varieties as a function of farmer and farm characteristics might increase adoption rates. Third, strengthening partnerships with service providers stimulates adoption. Finally, strengthening social group activities increases the spread of information and geographical diffusion of HIB. These activities will continue to support HarvestPlus' delivery strategy of biofortified staple food crops to the most vulnerable population in rural areas of Rwanda.

Appendix: Multiple Correspondence Analysis (MCA)

Multiple correspondence analysis (MCA) was performed to create two composite indices: the wealth index and the management index. The first composite index aims to measure household wealth in the absence of data on household income. The second composite index aims to summarize farmers' management practices. The former includes household, livestock, and agricultural assets. The later includes management practice activities, including whether the farmers have irrigation systems and apply pesticides, compost, manure, and fertilizers on their plots. Construction of these indices helped to control for multicollinearity.

In a nutshell, MCA is the application of a correspondence analysis algorithm to multivariate categorical data coded in the form of an indicator matrix (binary coding of the factors) that consists of an individual × variables matrix, where the rows represent individuals and the columns represent categories of the variables (Asselin 2009). For instance, the wealth index ranks households from poorest to wealthiest. Each household is given an individual wealth index, summarized below.

The functional form to build a composite indicator is as follows:

$$\text{CWIi} = \frac{1}{k}\sum_{k=1}^{k}\sum_{Jk=1}^{Jk} W_{Jk}^{k}\, I_{j_k i}^{k}$$

$$W_{j_k}^{k} = \frac{s^k}{\sqrt{\lambda_1}},$$

where k is the number of dimensions (variables) with k = (1, 2, …, K), j is the number of modalities of each dimension with j = (1, 2, …, J_k) and I is the binary (0/1) indicator of each modality. W is the weight determined with MCA (the factor score on the first axe normalized by the eigenvalue λ with s = factor score), and I is the index number indicating household.

The composite indicator is the simple average across dimensions (variables) of the weighted sum of each binary modality of each dimension.

Ip = binary indicator 0/1; 1 indicates household h has the modality, otherwise 0.

W_i = the average global welfare of household h.

There are three categories included in the wealth index: household assets, livestock assets, and agricultural assets. Household assets include land, houses, motorcycles, bicycles, cells, radios, TVs, saving accounts, and savings in informal groups. Livestock assets are sheep, goats, cattle, pigs, chicken, rabbits, etc. Agricultural assets include ploughs, wheelbarrows, machetes, shovels, picks, and sprayers.

Variables included in the management index are whether or not farmers have a terraced plot or irrigated plot, and whether or not they apply fertilizers, manure, compost, and pesticides.

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