Spatial Patterns of Technology Diffusion: The Case of Hybrid Rice in Bangladesh

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Abstract

In this paper we demonstrate a method for measuring the effect of spatial interactions on the adoption of hybrid rice using a unique, nationally-representative data set from Bangladesh. Based on resulst from a generalized spatial two-stage least squares estimation, we have shown that neighbor effects are a significant determinant of hybrid rice adoption. Further, using two specifications of spatial systems, we show that having a network including nearby hybrid rice adopters is more influential than having a network of more distant hybrid rice adopters, and that merely have a network with a large number of adopters may be relatively meaningless if they are far away.

JEL classification: O13, O33, Q12

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1 Introduction

Rice is a particularly important agricultural commodity in Bangladesh. Roughly 92 percent of farming households cultivate rice to some degree or another, with nearly 78 percent of cultivable area devoted to rice. As a result, rice comprises a significant source of caloric consumption for a large proportion of the population, representing nearly 70 percent of per capita daily caloric intake. Despite the very high importance of rice as a component to Bangladeshi livelihoods, rice productivity growth has stagnated since the mid-1990s. Yet there remains significant potential to increase overall rice production through the increased adoption of hybrid rice, many varieties of which provide significant yield advantages over traditional and even modern high yielding varieties. Increasing the cultivation of hybrids has the potential to have significant benefits for the livelihoods of both rural farming households as well as urban consumers. For farming households, the higher yields will provide an increased marketable surplus, which can raise farm incomes. For urban consumers, the increased supply of rice arising from widespread adoption of hybrids can lower food prices, especially for rice and its complementary goods, which are staple components of the diet of most households in Bangladesh.

Despite these potential benefits, hybrid rice adoption remains relatively low. As of 2009-10, only 6 percent of total agricultural area was used to cultivate hybrid rice (Rashid et al., 2011). Among other factors, information limitations, credit constraints, liquidity constraints, and supply side constraints remain significant barriers to the widespread uptake of new agricultural technologies. These constraints may be especially binding in subsistence or quasi-subsistence settings where input decisions and output consequences have immediate impacts on livelihoods.

The present study examinines spatial dimensions of hybrid rice adoption. We utilize data drawn from a nationally-representative household survey in Bangladesh to demonstrate that social interactions within a spatial context (i.e., observations on hybrid rice adoption behavior from members of defined neighborhood strucutures) are important determinants of hybrid rice adoption. Our identification and estimation strategy attempts to overcome the "reflection problem" by employing a generalized spatial two-stage least squares procedure that uses near-ideal instruments, allowing us to more effectively identify causal influences arising from social interactions. We also control for the additional correlations of unobservable characteristics which may condition adoption behavior. The resulting empirical framework allows us to more effectively decompose endogenous behavioral factors arising from social networks and other correlated effects that arise from members of the same neighborhood group being exposed to the same external influences.

2 Literature Review

There is a rich literature studying the process of technology adoption. Among the factors linked with adoption include tenurial arrangements (Newbery, 1975), (Bardhan, 1979), farm size (Feder, 1980), (Weil, 1970), education (Foster and Rosenzweig, 1996; Huffman, 2001), credit constraints (Weil, 1970; Lowdermilk, 1972; Lipton, 1976; Feder and Umali, 1993; Dercon and Krishnan, 1996), information constraints (Schutjer and Van der Veen, 1977; Fischer and Lindner, 1980), risk (Sandmo, 1971; Srinivasan, 1972; Feder, 1980; Feder et al., 1985; Liu, 2013), and social networks and social learning (Foster and Rosenzweig, 1995; Conley and Udry, 2010; Duflo et al., 2006). Over the past few decades, there has been a great deal of emphasis on role of social effects in the adoption and dissemination of agricultural technologies. Throughout the sociological or psychological literature, there has long been a realization that social or peer influences have a powerful effect on behaviors (e.g., Ostrom, 2000). The old adage "birds of a feather flock together" highlights the extent to which the belief that group members tend to behave similarly has permeated the folk consciousness. While such realizations have persisted, there is not a clear consensus on the manner in which group membership influences behavior.

Manski (1993) suggested three hypotheses to explain the effect of group membership on an individual's behavior: endogenous effects, contextual effects, and correlated effects. Endogenous effects reflect the fact that individual behavior influences the average group behavior (or individual group members' behavior) while at the same time being influenced by group behavior (or by the behavior of individual group members). Contextual (or exogenous) effects reflect the fact that an individual's behavior can be directly influenced by the exogenous characteristics of his or her group (or by those of individual group members). Correlated effects reflect the fact that individuals within a group behave in a similar fashion because they tend to have similar characteristics or otherwise face similar political, institutional, or environmental conditions. Within the context of agricultural technology, endogenous effects would capture the fact that an individual's adoption of a particular technology is largely influenced by the adoption patterns of other farmers in his or her social network (e.g., family, village, cooperative group, etc.), but the farmer's practices similarly affect the practices of all other members in his or her network. Underlying agricultural or environmental conditions, such as soil characteristics, climate, or agricultural policies would be examples of correlated effects, since these are often unobserved determinants of technological choice, but would be correlated across members of a particular network. When it comes to the adoption of new agriculutral technologies, the role of contextual effects is less clear. For example, contextual effects might condition technology adoption if, for example, an individual's adoption were conditioned by the overall (or average) socioeconomic status of the network (e.g., aggregate measures such as average income level). But it may be more appropriate to imagine that these contextual effects do not have any direct effect on technology adoption, but only affect adoption decisions indirectly, through their disaggregated effect on individual behavior, which then has direct endogenous effects. Our identification strategy is based on this premise.

The disentangling of the different social influences is important because of the varied policy implications of their respective existence. The existence of endogenous effects, for example, introduces a social multiplier effect arising from feedback mechanisms. Policies that directly influence one individual's behavior, for example, indirectly affects the behavior of other members of his or her social network, which in turn subsequently affect the individual, and can thus provide an avenue whereby investments can more efficiently result in the desired behavioral changes or improvements to social welfare. Contextual and correlated effects, on the other hand, do not have such multiplier effects, since there are no feedback loops between the effect and behaviors that policymakers can capitalize on.

It was long thought that the dissemination of agricultural technologies through extension services was sufficient to guarantee widespread adoption among farmers. More recent evidence, however, shows that learning from one's own experiences and learning from the experiences of others represent significant channels through which technologies disseminate amongst farmers. Many farmers adopt technologies after leaning from their peers or after witnessing a successful experience from a neighbor or friend. Also, it is the case that many farmers prefer to get advice from their peers with regards to fertilizer, pesticides, herbicide application or type of varieties to grow. There are several examples supporting the neighborhood influence in agricultural technology adoption. For instance, Case (1992) shows that farmer's adoption of sickle in Indonesia for rice farming is dependent upon neighboring farmer's success with that technology. Bandiera and Rasul (2006) show that farmer's adoption decisions of sunflower in Mozambique are correlated with the choices of their network of family and friends, but they are uncorrelated with the decisions of those in different religions. Similarly, Conley and Udry (2010) find in their study in Ghana that pineapple farmers adjust their inputs to align with those of their information neighbors who were successful in previous periods. Among others, the spread of new varieties across farmers represents an example where the role of farmers-to-farmers interaction is particularly important. In most agricultural projects new seed varieties are usually introduced to few farmers, usually the progressive farmers who are willing to take the risk, with the expectation that other farmers will also adopt. Social network through household and plot neighborhood, kinship, friendship or religion facilitate the dissemination of varieties through farmers. For instance, adoption of a new high yielding variety to replace a low yielding traditional one will happen when farmers are convinced about its good traits and better characteristics. In order for this to happen, knowledge spillovers and learning externalities from peers facilitate the trust building about the new technology. Foster and Rosenzweig (1995) show that farmers with experienced neighbors are significantly more profitable than those with inexperienced neighbors. Holloway et al. (2002) find a positive and significant neighborhood effect on high yielding variety adoption in Bangladesh. Using a spatial tobit estimator to control for the censored nature of improved maize adoption, Langyintuo and Mekuria (2008) find evidence not only that neighbors' adoption influences farmers' adoption, but also that membership in farmer associations and contact with extension officers positively affect adoption of these improved varieties. Social interactions and social learning could therefore facilitate increased productivity growth by fostering the spread of improved technologies within social networks.

Even though the role of social networks, social learning and knowledge spillovers for technology adoption is widely advocated in the literature, the econometric methodologies used for this investigation are quite diverse. Based on a simple model in which the endogenous, contextual, and correlated effects are represented as group means, Manski (1993) demonstrated the strong assumptions that must be made in order to sufficiently identify the social effects. Without such strong assumptions, one cannot generally separate the endogenous effects from the contextual effects. Social networks, social learning, neighborhood effects and knowledge spillovers entail consideration of spatial effects, but most previous studies of technology adoption have failed to appropriately model these effects in their econometric approach. Staal et al. (2002) noted that household level statistical analyses of technology adoption have long failed to properly account for effects of spatial spillovers in technology adoption by using rudimentary conventional proxies such as regional dummy variables, distances to urban or market centers. When spatial effects–particularly spatial autocorrelation–exist and they are not appropriately accounted for, or estimated with adequate regression methods, estimates could be affected, either through bias or inconsistency. Manski (1993) considered endogenous effects models that take the form of spatial correlation models, noting that a simple two-stage estimation procedure could be used to estimate pure endogenous effects models. Such a two-stage procedure involves first estimating the endogenous effect regression non-parametrically, and then including this first-stage estimate as an additional regressor in a second-stage least squares regression. But such a pure effect model explicitly assumes the absence of spatial correlations among unobservable factors, which almost certainly play a significant role in conditioning technology adoption.

3 Background on Hybrid Rice and the Bangladesh Experience

Hybrid rice arises from crossing genetically distinct parental lines, one of which (the male) is sterile. The result of the hybridization process is heterosis, or hybrid vigor, which is characterized by the increase in yield, uniformity, or vigor of cultivated plants. Hybrids exhibit several characteristics that differentiate them from other, self-pollinating varieties. These differences complicate farmers' decisionmaking calculus. First, hybrid rice often produces yields in excess of even modern high-yielding inbred varieties, often 15-30 percent higher. In addition, because of hybrid vigor and uniformity, hybrids require a lower seeding rate than inbred varieties, usually in the neighborhood of 67 less seed per acre. Heterosis declines dramatically and eventually disappears in subsequent generations, due to the segregation of dominant and recessive alleles. Thus, the primary advantages of hybrid plants–including increased yields–are largely restricted to first generation seeds. To continually realize the yield gains vis-á-vis varieties, farmers must purchase new first generation hybrid seed on a seasonal basis. But first generation hybrid seeds are considerably more expensive than seeds of inbred varieties, even modern high-yielding varieties. Farmers must therefore weigh the benefits of increased yield and seed efficiency with the costs of higher seed prices and the inability to save harvested grain to be re-used as seed in subsequent seasons.

While Bangladesh is one of the most densely populated countries in the world, the population is largely rural. Agricultural production is the backbone of rural livelihoods for virtually all rural households in Bangladesh. Nearly 44 percent of the labor force is employed in the agriculutural sector, which contributes roughly 20 percent of gross domestic product. Far and away, the most important agricultural commodity is rice. Roughly 92 percent of farming households cultivate rice to some degree or another, with nearly 78 percent of total cultivable area devoted to rice. In Bangladesh, rice is cultivated in three seasons: aus (April–July/August), aman (July–December) and boro (December–May). Most land in Bangladesh is either single-cropped (during either aman or boro) or double-cropped (during both boro and aman), with a small minority triple-cropped (aman, boro, and aus). While traditionally the main rice growing season has been the aman (monsoon) season, this has changed in recent decades, largely due to liberalization and other supportive policies that have increased the proliferation of small-scale irrigation equipment for use during the predominantly dry boro season. From 1996 to 2005, boro rice area increased from 30 percent to 40 percent of total rice area, while its share of total rice production increased from 39 percent to 55 percent (Table 1). From 2005 to the present, while total boro production has increased, its share of total has held steady at 55 percent.

Somewhat surprisingly, hybrids in Bangladesh are primarily cultivated during the boro season. This is largely a historical coincidence (Spielman et al., 2012). Unlike the case in neighboring India, the hybrid seed system in Bangladesh has in large part depended upon imported material from

China. Hybrid rice first entered the Bangladesh market during boro 1999, when several private sector companies imported roughly 2,000 metric tons of hybrid seed from China to supplement shortfalls in domestic seed supply caused by floods in 1998 (Azad et al., 2008). Subsequently, several private sector seed companies began importing hybrid parental lines for domestic seed production, rather than simply importing the seeds directly. By 2007, nearly 10,000 metric tons of hybrid seeds were used in Bangladesh, with only 77 percent of the total hybrid seeds used coming as direct seed imports (Hossain, 2008). While adoption of hybrid rice was initially quite slow (due to a number of factors, not the least of which is supply constraints), the pace of adoption increased in the first decade of the millenium, reaching as high as 9 percent of total area (22 percent of total boro area) in 2007 (Rashid et al., 2011).

4 Theory

There are several common ways for modeling the process of technology adoption. Foster and Rosenzweig (1995) specify a target input model and incorporate a Bayesian learning process to model adoption of high-yielding varieties (HYVs) in India. In their model, the optimal input level is unknown, and each application of the technology represents a trial which yields additional information regarding the distribution of random productivity disturbances characterizing this optimal input level. This approach contrasts with the approach taken by Besley and Case (1994), who instead assume that the profitability of a particular technology is stochastic, and it is only through experimenting that one uncovers the distribution of profits attainable by adoption. Conley and Udry (2010) model an uncertain production technology subject to productivity shocks, with production technology the object of learning. Farmers update their beliefs regarding production technology only after observing neighbors' past input usage, growing conditions, and realized output. To demonstrate the importance of social influences on production decisions, consider a variant of the learning model introduced in Conley and Udry (2010). We consider an agricultural season comprised of two time periods: farmers make input decisions in period t and realize output in period

$t+1$. Realized output (per unit of land) can be written

$$y_{i,t+1} = f(x_{it}; \upsilon_t) + \varepsilon_{i,t+1}(\upsilon_t) \tag{1}$$

where $y_{i,t+1}$ is realized productivity in the future, x_{it} is the quantity of input used (per unit of land) in the current period, $\varepsilon_{i,t+1}$ is a mean-zero stochastic productivity shock that is independently and identically distributed across farmers, and υ_t characterizes growing conditions. Note that we have written equation (1) such that current growing conditions affect both the input response (production) function as well as the exogenous, stochastic productivity shock. Farm profits can be written

$$\pi_{i,t+1} = p_{t+1}y_{i,t+1} - r_t x_t = p_{t+1}\left[f(x_{it}; \upsilon_t)\right] - r_t x_{it} \tag{2}$$

where p_{t+1} are future output prices and r_t is the current unit price of input x. Because future output prices and productivity are stochastic, farmers do not know what either productivity or farm profits will be in the future based simply on decisions they make in the present. Rather, we assume that farmers have some understanding about the distribution of productivity given their input use and current growing conditions. Expectations in period t regarding future profits can be written

$$E_{it}\left[\pi_{i,t+1}\right] = E_{it}\left(p_{t+1}\right) E_{it}\left[f\left(x_{it}; \upsilon_t\right)\right] - r_t x_{it} \tag{3}$$

The farmer's profit maximization problem in period t is therefore

$$\max_{x_{it}} E_{it}\left[\pi_{i,t+1}\right] = E_{it}\left(p_{t+1}\right) E_{it}\left[f\left(x_{it}; \upsilon_t\right)\right] - r_t x_{it} \tag{4}$$

The expected profit maximizing level of inputs is therefore

$$x_{it}^{*} = \arg\max_{x_{it}} \left\{E_{it}\left(p_{t+1}\right) E_{it}\left[f\left(x_{it}; \upsilon_t\right)\right] - r_t x_{it}\right\} \tag{5}$$

So, therefore, the expected profit under this optimal input level is at least as high as the expected profits from any other possible input choice:

$$E_{it}(p_{t+1})E_{it}\left[f(x_{it}^*;\upsilon_t)\right] - r_t x_t^* \geq Eit(p_{t+1})E_{it}\left[f(\tilde{x}_{it};\upsilon_t)\right] - r_t\tilde{x}_t, \quad \forall \tilde{x}_{it} \neq x_{it}^* \tag{6}$$

The process of formulating and updating subjective expectations about productivity is an important and interesting process. We assume that current expectations are a function of both one's own experiences (i.e., realized profits) as well as the experiences of other farmers within one's social network. Expected productivity can be written

$$E_{it}\left[f\left(x_{it};\upsilon_t\right)\right] \equiv E_{it}\left[f\left(x_{it};\upsilon_t\right)|Y_{it}(X_i), Y_{jt}(X_j), \Upsilon_t\right] \quad \forall j \in J \tag{7}$$

In this identity, $Y_{it}(X_i) = y_{it}(x_{i,t-1}), y_{i,t-1}(x_{i,t-2}), ..., y_{i,t-T+1}(x_{i,t-T})$ summarizes farmer i's memory in period t of his own input decisions and observed next-period output (to the extent of his memory, T), $Y_{jt}(X_j) = y_{jt}(x_{j,t-1}), y_{j,t-1}(x_{j,t-2}), ..., y_{j,t-T+1}(x_{j,t-T})$ summarizes farmer i's memory in period t of the input decisions and observed next-period profits of neighbor $j \in J$, where J is the set of all members in farmer i's social network, and $\Upsilon_t = \upsilon_{t-1}, \upsilon_{t-2}, ..., \upsilon_{t-T}$ reflects farmer i's memory in period t of past growing conditions. At time t, therefore, farmer i observes the productivity (and hence profit) of input choices $x_{i,t-1}$ and $x_{j,t-1}$. These observations have impacts on current expectations. We assume that expected productivity is increasing in positive deviations in observed past productivity from prior expectations, whether from farmer i himself or a member of his social network. Let $E_{it_0}\left[f(x_{it};\upsilon_t)|Y_{i,t-1}(X_i), Y_{j,t-1}(X_j), \Upsilon_{t-1}\right]$ represent baseline prior expectations in period t before observing $y_{it}(x_{i,t-1};\upsilon_{t-1})$ or $y_{jt}(x_{j,t-1};\upsilon_{t-1})$ $\forall j \in J$. Then let $\Delta E_{it}\left[f(x_{it};\upsilon_t)\right] \equiv E_{it}\left[f(x_{it};\upsilon_t)|Y_{it}(X_i), Y_{jt}(X_j), \Upsilon_t\right] - E_{it_0}\left[f(x_{it};\upsilon_t)|Y_{i,t-1}(X_i), Y_{j,t-1}(X_j), \Upsilon_{t-1}\right]$ represent the updating of farmer i's expectations based on observing outputs y_{it} and y_{jt}, $\forall j \in J$. For first-time adoption, $Y_{it}(X_i) = 0$, so $E_{it}\left[f(x_{it};\upsilon_t)\right] \equiv E_{it}\left[f(x_{it};\upsilon_t)|Y_{jt}(X_j), \Upsilon_t\right]$, and $\Delta E_{it}\left[f(x_{it};\upsilon_t)\right]$ will have the same sign as $\pi_{jt}(x_{j,t-1};p_t, r_{t-1}, \upsilon_{t-1}) - E_{it_0}\left[\pi_{jt}(x_{j,t-1})\right]$ (Conley and Udry, 2010). But this need not be the case for continued use of a particular technology. Since expectations are a function of learning by doing and learning from others, it could be the case that farmer i's own past experiences result in $\Delta E_{it}\left[f(x_{it};\upsilon_t)\right] > 0$, even under cases where $\pi_{jt}(x_{j,t-1}, p_t, r_{t-1}; \upsilon_{t-1}) < E_{it_0}\left[\pi_{jt}(x_{j,t-1})\right]$. The converse is also possible. Additionally, we will assume that learning is local, so that $\Delta E_{it}\left[f(x_{it};\upsilon_t)\right] |Y_{it}(X_i), Y_{lt}(X_l), \Upsilon_t = 0$ for $l \notin J$.

Combining equations (5) and (7), we can write a reduced form hybrid rice adoption decision equation as

$$x_{it} = g(E_{it}(p_{t+1}), Y_{it}(X_i), Y_{jt}(X_j), \Upsilon_t, r_t; Z_{it}) \tag{8}$$

Each of the terms in this reduced form equation have been introduced before, with the exception of Z_{it}, which is a vector of household-specific characteristics. We introduce these terms to demonstrate idiosyncratic differences that may lead to differences in hybrid adoption between otherwise observationally equivalent farmers. For example, there may be household-specific demographic, sociological, economic or ecological characteristics that may condition technological adoption decisions. Feder (1980) for example has demonstrated that farm size, risk preferences, and access to credit may be important determinants of agricultural input decisions. Given the presentation of equation (8) as a reduced form demand equation, these variables may be viewed as idiosyncratic demand shifters. This reduced form equation provides us with the basic empirical model for this exercise.

5 Empirical Methods

Farmers' adoption of a new technology is often modeled through a limited dependent variable econometric model. The most common approach is to specify a binary dependent variable model, such as a probit or a logit model (Feder et al., 1985). Such an approach allows the researcher to identify those factors that affect adoption in a probabilistic setting: X increases the probability that y will be adopted. If social interactions facilitate technology adoption, then an important explanatory variable included on the right hand side of any regression equation would be spatially-lagged dependent variables: $\sum_{j\in J}\omega_{ij}y_j$, where J captures i's network, ω_{ij} represents the (i,j) element of a properly specified spatial weights matrix, and y_j is the observation of y for network member $j \in J$, $j \neq i$. In matrix terms, this is written as Wy, where W is some $N \times N$ spatial weights matrix that defines the structure of the spatial setting (i.e., the "neighborhood" within which members exert influence over one another) and y is an N-vector of observations on the dependent variable. In this case, $y_i \in y$, but since the diagonal elements of W are zero, $\omega_{ii}y_i$=0, so there are no "own influences".

As Manski (1993) observed, behaviors among members of a group may be similar because such group members have similar characteristics or because they are exposed to similar institutional or contextual environments. If these individual characteristics or characteristics of the institutional or contextual environments are not directly observed or controlled for, then the correlation among these factors across individuals within a particular group may decrease the efficiency of estimates of other observable effects. In other contexts, (e.g., when sample selection bias is a concern) the failure to control for such correlations among unobservables has been shown to bias coefficient estimates.

With these modifications established, we can specify our econometric model based on equation (8) as

$$\begin{aligned} H_i &= \alpha + \rho \sum_{j \in J_i} \omega_{ij}^1 H_j + z_i' \beta + \epsilon_i \\ \epsilon_i &= \lambda \sum_{j \in J_i} \omega_{ij}^2 \epsilon_j + u_i \end{aligned} \tag{9}$$

where $H_k,\ k = i, j$ is a binary hybrid rice adoption measurement corresponding to farmer i and network member j, z_i is a vector of household characteristics, u_i is an random error term, and ω_{ij}^m is the (i, j) element of the m^{th} spatial weights matrix W^m. The ρ and λ terms are spatial correlation coefficients (also commonly referred to as spatial autoregressive parameters) corresponding to spatially lagged dependent variables and errors, respectively. The parameter space for these parameters is typically taken to be the interval (-1,1). This model is a variant of the standard Cliff-Ord model (Cliff and Ord, 1981), with the addition of a spatial process amongst unobservables. In the language of Anselin (1995), we refer to this model as a first-order spatial autoregressive model with first-order spatial autoregressive disturbances, or SARAR(1,1) for short. Given the complexities of the econometric modeling, we specify the binary dependent variable model as a linear probability model.

The first row of equation (9) implies that household i's hybrid rice adoption is a function of i's neighbors' adoption as well as i's exogenous characteristics. Variables included in z would be features of household demographic characteristics (e.g., household composition, characteristics of the household head, etc.) and economic characteristics (e.g., income or expenditures, savings, occupational characteristics, etc.). The second row of equation (9) captures spatial correlation in unobservable factors, also referred to as spatially lagged errors or spatial autoregressive errors. Several previous researchers have acknowledged the existence of such correlations affecting technology adoption decisions (e.g., Bandiera and Rasul, 2006), but there have been relatively limited efforts to address them (Conley and Udry, 2010 are a notable exception).

6 Identification Strategy

Our empirical exercise is faced with a nontrivial identification challenge related to the identification of social learning effects. In a cross-sectional setting, we are unable to directly identify the impacts of learning from others, since spatially-lagged adoption observations are correlated with the unobserved error term u_i in equation 9. In this regard, our identification problem is the general identification problem in social interactions, what Manski (1993) referred to as the 'reflection' problem. In its general form, we are unable to infer causal relationships in hybrid rice adoption, merely spatial correlations in adoption behavior. We cannot disentangle whether household i's behavior is directly influenced by the behavior of the members of i's social network, whether behaviors are simply correlated because of other unobservable factors, or whether we estimate correlations arising from household i's behavior influencing the behavior of the members of i's social network. We are unable to control for the timing of hybrid adoption (as Conley and Udry, 2010 are able to do in their study of pineapple adoption in Ghana). Because of this limitation, we are unable to directly attribute social influences in hybrid rice adoption from early adopters to later adopters without an appropriate identification strategy.

Our identification of learning effects relies upon an approach initially introduced by Kelejian and Prucha (1998) and later modified by Arraiz et al. (2010) and Kelejian and Prucha (2010) into a IV/GMM generalized spatial two-stage least squares. We can re-write equation (9) in matrix notation (for a sample of size N) as

$$\begin{aligned} H_N &= \rho_N W_N H_N + Z_N \beta_N + \epsilon_N \\ \epsilon_N &= \lambda_N W_N \epsilon_N + u_N \end{aligned} \tag{10}$$

which can be written as

$$\begin{aligned} H_N &= M_N \delta_N + \epsilon_N \\ \epsilon_N &= \lambda_N W_N \epsilon_N + u_N \end{aligned}$$

with $M_N = [W_N H_N,\ Z_N]$ and $\delta_N = [\rho_N,\ \beta_N']'$. Kelejian and Prucha (2010) propose a two-step procedure for efficiently estimating all of the model parameters, with sub-procedures in each step. In the first step, the model is estimated by two-stage least squares (2SLS) using the instruments Q_N. The autoregressive parameter λ_N is estimated based on the 2SLS residuals using the generalized moment approach initially introduced in Kelejian and Prucha (1999). This estimate of λ_N is consistent, but inefficient. In the second step, the original model is transformed via a spatial Cochrane-Orcutt transformation accounting for the estimated λ_N, and this transformed model is estimated by generalized spatial 2SLS (GS2SLS). The GS2SLS residuals are then used to obtain a consistent and efficient estiamtor for λ_N.

Consider the endogenous regressor $W_N H_N$. Note that, so long as the eigenvalues of W_N are all less than one, $E\left(H_N\right) = \left(I_N + \rho_N W_N + \lambda_N^2 W_N^2 + ...\right) Z_N \beta$. The ideal instrument for $W_N H_N$ is therefore $E[M_N] = [Z_N, W_N E\left(H_N\right)]$. Given that $E\left(H_N\right)$ is an infinite series, we can approximate for the ideal instrument. Let Q_N be the $N \times p$ instrument matrix used to instrument M_N. We specify Q_N as a subset of the linearly independent columns of $E(M_N)$, such that $Q_N = \left[Z_N, W_N Z_N, W_N^2 Z_N^2\right]$. Then we can write P_Q as the projection matrix $P_{Q_N} = Q_N \left(Q_N' Q_N\right)^{-1} Q_N$. The first step 2SLS estimator for $\tilde{\delta}_N$ is

$$\tilde{\delta}_N = \left(\hat{M}_N' M_N\right)^{-1} \hat{M}_N' H_N \tag{11}$$

where $\hat{M}_N = P_{Q_N} M_N = Z_N \hat{W_N H_N}$ and $\hat{W_N H_N} = P_{Q_N} W_N H_N$. The 2SLS residuals $\tilde{u}_N = H_N - M_N \tilde{\delta}_N$ are used in an GMM estimator (Kelejian and Prucha, 1999) to consistently estimate the spatial error coefficient, denoted $\tilde{\lambda}$. This estimate is then used to transform the original model.

It can easily be seen that $\epsilon_N = (I_N - \lambda_N W_N)^{-1} u_N$, so we can write this model as

$$H_N^* (\lambda_N) = M_N^* (\lambda_N) \delta + u_N$$

where $H_N^* (\lambda_N) = H_N - \lambda_N W_N H_N$ and $M_N^* (\lambda_N) = M_N - \lambda_N W_N M_N$; these variables have undergone a spatial Cochrane-Orcutt transformation, which can be achieved by simply pre-multiplying by $(I_N - \lambda_N W)$.

With consistent (but inefficient) estimates $\tilde{\lambda}$, we define our generalized spatial 2SLS (GS2SLS) estimator for δ using this spatial Cochrane-Orcutt transformation:

$$\hat{\delta}_N \left(\tilde{\lambda}_N \right) = \left[\hat{M}_N^* \left(\tilde{\lambda}_N \right)' M_N^* \left(\tilde{\lambda}_N \right) \right]^{-1} \hat{M}_N^* \left(\tilde{\lambda}_N \right)' H_N^* \left(\tilde{\lambda}_N \right) \tag{12}$$

where $\hat{M}_N^* \left(\tilde{\lambda}_N \right) = M_N - \tilde{\lambda}_N W_N M_N$, $\hat{H}_N^* \left(\tilde{\lambda}_N \right) = H_N - \tilde{\lambda}_N W_N H_N$, and $\hat{M}_N^* \left(\tilde{\lambda}_N \right) = P_{Q_N} M_N^*$. The re-computed GS2LS residuals are then used as the basis for an efficient GMM estimation of λ_N.

This identification strategy assumes that the only effect of spatially-lagged explanatory variables on hybrid rice adoption is through their effect on neighbors' adoption decisions. In other words, since $W_N Z_N$ and $W_N^2 Z_N^2$ are used as instruments in our estimation, we must assume that $\mathrm{corr}\,(H_N, W_N Z_N) = 0$, and that there are no contextual effects conditioning hybrid rice adoption. While Manski (1993) suggested that individual behaviour could be swayed by the average characteristics of members of his social network, it may be justifiable to assume that the average level of education, for example, should not affect an individual's adoption of hybrid rice *except* insofar as higher average levels of education lead to higher average levels of hybrid rice adoption in the network. So the causal chain runs from neighbors' higher levels of education leading to neighbors' higher rates of hybrid adoption, which in turn leads to increased adoption for the individual in question. Thus, we feel the assumption is justified and omit any cross-regressive terms that would capture these contextual effects.

7 Data

The data used in this study come from the Bangladesh Integrated Household Survey (BIHS), a nationally-representative household survey conducted by researchers from the International Food Policy Research Institute (IFPRI) in October and November 2011 as part of the Bangladesh Policy Research and Strategy Support Program (PRSSP). The survey represents the most comprehensive nationally-representative survey ever conducted in Bangladesh (Ahmed, 2013). The survey utilizes a multi-stratum sampling approach, with sub-national divisions representing a separate stratum. The samples drawn from each division, therefore, are representative of rural areas in that division. In the first stage of sampling, the total sample of 325 primary sampling units were allocated among eight primary strata with probability proportional to size (where size is the number of households in each stratum). In the second stage, 20 households were randomly selected from each primary sampling unit. We restrict our sample to households with a nonzero area of cultivated land, yielding a sample of 2612 households. The location of households included in our sample are shown in Figure 1. As can be seen from this figure, the households are widely distributed throughout Bangladesh.

Some caveats must be addressed regarding the use of these data to address a complicated issue such as this. First, given the cross-sectional nature of our data, we are unable to control for a household's previous experiences with hybrid rice, nor are we directly able to observe causality in terms of neighbors influence on technology adoption. Specifically, we do not know whether the household has cultivated hybrid rice before or how any such experiences panned out in terms of yield or profits. These omitted variables are subsumed into the idiosyncratic disturbance terms, and given the correlation between farmer i's experiences and farmer j's hybrid rice adoption decisions (which are observed and are controlled for in our econometric specification), there is the issue of endogeneity which would result in biased estimates for the network effect. Unfortunately, we are unlikely to find a suitable instrument for omitted own-experiences, since any variable that would be correlated with own-experiences would also be correlated with current hybrid rice adoption, and should therefore be included as an explanatory variable in the model.

Second, there are are challenges in identifying neworks. Any attempt at analyzing social influences in behavior must somehow define the social system, which is a nontrivial matter. The challenges associated with measuring and specifying social networks has become a topic of particular interest in recent years (see, e.g., Maertens and Barrett, 2012; Chandrasekhar and Lewis, 2011). This is perhaps particularly tricky with survey data. Even though the BIHS is designed to be nationally representative, it is still a sample and not the entire population. Thus specifying a social system with the BIHS undoubtedly omits members that are potentially relevant in conditioning behavior. We openly acknowledge this shortcoming, yet suggest that the representativeness of the data at least allow us more flexibility in observing aggregate or average network effects, though not direct individual effects. With that caveat, we proceed to specify our spatial/social system in two different fashions. First, we use household GPS coordinates to construct a system in which the strength of network relationships is inversely (squared) related to the actual physical distance between households.[1] Second, we define a system in which all households within a particular village are considered network members. This latter system takes the form of a simple Boolean matrix, allowing each member of i's network to exert an equivalent influence on i's behavior, regardless of the actual distance between them. In what follows, these spatial/social systems are defined by W_1 and W_2, respectively, where W_1 and W_2 are each $N \times N$ symmetric weights matrices with 0s on the diagonal, and where the off-diagonal elements define the strength of the social engagement between the household represented by row i and the household represented by column j.

We are interested in studying the effects of spatial factors–including social interactions–on hybrid rice adoption. Before proceeding with regression analysis, we undertake some simple exploratory spatial data analysis to determine if there are significant spatial patterns of hybrid rice adoption. Figure 2 illustrates the pattern of hybrid rice adoption at the district level in Bangladesh. From this figure, there certainly appear to be spatial patterns of hybrid rice adoption, with high rates of adoption occurring in the northwestern Rajshahi and Rangpur divisions and the southeast Chittagong division, and low rates of adoption in the central division of Dhaka and the southern divisions of Barisol and Khulna. Forgoing potentially unrealistic assumptions of global stationarity, we compute local statistics to test for clustering or spatial correlation in hybrid rice adoption. These local indicators of spatial association (Anselin, 1995) indicate significant spatial relationships in the rates

[1] So as to maintain an invertible weights matrix, we first define a threshold band within which these inverse distance weights are applied.

of hybrid rice adoption in several districts, including Nilphamari and Rangpur districts in Rangpur division and Jaipurhut district in Rajshahi division.[2]

We can also test for unconditional spatial relationships at the household level. Given a binary hybrid rice adoption term (H), we can use join count tests to test for spatial patterns of adoption ($H = 1$) and non-adoption ($H = 0$) based on specification of our spatial system. Such tests have a null hypothesis of no indicate significant spatial relationships between adoption and non-adoption. Table 2 reports the results of join count tests based on the two specifications of the spatial/social environment. We find very strong evidence of correlations of hybrid rice adoption behavior amongst members of our defined spatial systems–both adoption and non-adoption.

To test for the conditional influence of social interactions, we introduce a series of explanatory variables assumed to impact household hybrid rice adoption decisions. These household characteristics include the age of the household head; agricultural land area; a binary variable capturing access to credit (equal to 1 if the household has ever had a loan, 0 otherwise); a binary variable capturing whether external parties are able to exert influence on agricultural decisions, including crop choice and input use (equal to 1 if there is such an external influence, 0 otherwise); dependency ratio (share of dependents to working age household members); number of migrants in the household; a binary variable equal to 1 if the household head is literate, 0 otherwise; a binary variable equal to 1 if the primary occupation of the household head is farming, 0 otherwise; household assets (a plausibly exogenous proxy for household wealth); two measures capturing interactions with agricultural extension officers (includes both the number of times such officers contacted the household, as well as vice versa); a binary variable indicating whether the household has experienced crop losses as a result of flood, drought, storms, pests, diseases, or other reasons; and a binary variable capturing whether the household receives a subsidy for rice production.[3] Summary statistics for these data along with summary statistics for hybrid rice adoption are presented in Table 3.

[2]This statistic is calculated as $I_i = \frac{(x_i - \bar{x})}{\sum_{k=1}^{n}(x_k - \bar{x})^2/n} \sum_{j=1}^{n} w_{ij}(x_j - \bar{x})$, where x_i is data for the observational unit in question, $\bar{x}$ is the average value of x for the spatial system under analysis.

[3]Controlling for the effects of external influences on crop choice and input decisions is designed to capture the effects of tenurial arrangements, since these have been attributed with delayed adoption of new agricultural technologies (Bardhan, 1979). Our measure of household assets is an index constructed using polychoric principal components analysis (Kolenikov and Angeles, 2009). We do not control for female-headed households due to the extreme paucity of such households in the sample.

8 Results

Table 4 reports the results of estimating equation 9 by IV/GMM allowing for heteroskedasticity of an unknown form. These results reveal some interesting insights, particularly regarding neighborhood influence on hybrid rice adoption. The spatial lag parameter ρ is both positive and significant, regardless of the weights matrix specification. This confirms assumptions that there is a great deal of spatial correlation in hybrid rice adoption behavior. However, the magnitude of the influence is much higher with the inverse distance weights matrix. Given the similarity in the estimated coefficients for all of the other variables across the two specifications, we can be confident that the two specifications of spatial correlation are not capturing different information in the variability of hybrid rice adoption. Therefore, this appears to confirm Tobler's first law of geography, that near things are more related than distant things, or in our case, that closer network members have a greater influence on behavior than more distant network members. Based on an inverse distance weighting, $\omega_{ij}^1 = 1/f(d_{ij})$, where d_{ij} is the distance between network members i and j, and f is some function of the distances. In our specification $\omega_{ij}^1 = 1/d_{ij}^2$. So the effects of two network members j and k on farmer i's adoption of hybrid rice is such that $\omega_{ij}^1 H_j > \omega_{ik}^1 H_k$ for $d_{ij} < d_{ik}$. The Boolean weights matrix equally weights network members, and therefore $\sum_{j \in J} \omega_{ij}^2 H_j$ is the total number of hybrid rice farmers in i's network, and our estimate of ρ^2 captures the average effect of this sum. Since our estimate of ρ^1 using the inverse distance weights matrix captures the average effect of $\sum_{j \in J} \omega_{ij} H_j$, our results suggest the number of nearby hybrid rice farmers in one's network has a larger effect on hybrid rice adoption than merely the total number of hybrid rice adopters in one's network. While our results suggest that equally weighting network members' influence on behavior can capture social influences, such equal weighting may not be optimal. Rather, by demonstrating that closer network members exert a greater influence than more distant network members, these results suggests heterogeneously weighting network relationships can be an important strategy for improving future research on social networks. Distance weighting is an obvious strategy, but other types of weighting schemes could be considered. Regardless, it is safe to conclude that there is evidence of positive influence from neighbors in terms of adoption of hybrid rice, and this result is robust across different specifications.

Some other noteworthy findings arise from the results reported in Table 4. Farmer contact with extension officers (including both visits to extension officers as well as from) does not have a statistically significant effect on hybrid rice adoption. One interpretation of this result, given the positive and significant effect of network effects, is that perhaps farmers rely more on the experiences of their peers, and less on information provided them by extension officers. Even though the role of the extension officer is to inform and educate farmers on ways to increase productivity, including the use of modern varieties, learning from the experience of peers can still dominate farmers' decision to adopt the technology. Also worth mentioning is that interactions between farmers and extension officers usually entail discussions on a whole range of agronomic practices, not just seeds. The extent to which the extension officer's emphasize rice varieties (hybrid in this case) in his portfolio could be instrumental in farmers adoption decision. Additionally, this insignificant effect could reflect the fact that farmers are already largely aware of the technology. Indeed, data collected as part of the Cereal Systems Initiative for South Asia (CSISA) indicates that virtually all Bangladeshi farmers in their sample were familiar with hybrid rice.

Access to credit and subsidies also appear as significant determinants of hybrid rice adoption (the effect of rice subsidies is significant at the 11 percent level under the inverse distance weighting specification). Because hybrid seeds are dramatically more expensive than seeds for even modern high yielding rice varieties, credit and other cash constraints appear to be particularly problematic. Loosening these constraints by increasing access to credit and providing policy mechanisms such as subsidized seed prove beneficial in stimulating demand for these technologies.

9 Conclusion

In recent years there has been a growing in terest in studying the effects of social networks, including the effects of social networks in facilitating the adoption of new agricultural technologies in developing countries. But there are significant challenges in specifying and measuring social networks and social interactions, and significant econometric challenges for identifying such effects amid endogneous and spatially correlated effects that can confound interpretations.

In this paper we have demonstrated a method for measuring the effect of social networks on the adoption of hybrid rice using a unique, nationally-representative data set from Bangladesh. Our methodology allows for correlations in hybrid rice adoption amongst members of a specified network as well as correlations in unobservable factors that condition hybrid adoption. To overcome issues of endogeneity, our identification strategy relies on allowing spatially lagged hybrid rice adoption to be conditioned by a matrix of spatially lagged exogenous explanatory variables. Using a generalized spatial two-stage least squares estimator, we have shown that neighbor effects are a significant determinant of hybrid rice adoption in Bangladesh. Further, using two specifications of spatial systems, we have shown that having a network including nearby hybrid rice adopters is more influential than having a network of more distant hybrid rice adopters, and that merely have a network with a large number of adopters may be relatively meaningless if they are far away.

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Table 1: Rice area, production, and varietal diversity in Bangladesh

Season	Share of area %		Share of Production %		No. of Rice Varieties	
	1996	2005	1996	2005	1996	2005
Aus	24	10	16	6	440	295
Aman	46	50	45	49	519	535
Boro	30	40	39	55	143	261
All Seasons	100	100	100	100	100	100

Source: Hossain and Jaim (2012).

Table 2: Join count test results under alternative specifications of weights matrix

Join Count Test	Statistic	p-value	
$H = 0$, $W = W_1$	10.751	0.000	***
$H = 1$, $W = W_1$	17.924	0.000	***
$H = 0$, $W = W_2$	3.410	0.000	***
$H = 1$, $W = W_2$	40.607	0.000	***

Note: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Table 3: Summary statistics of variables included in empirical analysis

Variable	Mean	Std. Deviation	Minimum	Maximum
Hybrid Adoption (=1)	0.095	0.293	0.000	1.000
Household head age	45.513	13.397	18.000	95.000
Agricultural area	0.664	0.706	0.004	9.014
Access to credit	0.834	0.372	0.000	1.000
External decisionmakers	0.219	0.414	0.000	1.000
Dependency ratio	0.554	0.719	0.000	5.000
Migrants	0.036	0.206	0.000	4.000
Literacy of household head (=1)	0.463	0.499	0.000	1.000
Household head is a farmer (=1)	0.652	0.477	0.000	1.000
Household asset index	0.316	1.838	-3.024	11.054
Number of visits/contacts from extension officers	0.190	0.919	0.000	12.000
Number of visits/contacts to extension officer	0.106	0.706	0.000	20.000
Rice subsidy (=1)	0.107	0.309	0.000	1.000
Crop lossses in last 5 yrs	0.100	0.299	0.000	1.000

Table 4: IV/GMM Spatial ARAR(1,1) regression results

	Inverse Distance Weights		Village Binary Weights	
	Estimate	Std. Error	Estimate	Std. Error
Household head age	-0.0002	0.0002	-0.0003	0.0003
Agricultural area	0.0287***	0.0082	0.0412***	0.0094
Credit access (=1)	0.0224**	0.0098	0.0220*	0.0126
External influence on input decisions (=1)	0.0054	0.0112	0.0000	0.0143
Dependency ratio	-0.0076	0.0053	-0.0004	0.0066
Migrants	-0.0219	0.0154	-0.0279	0.0188
Literacy of household head (=1)	0.0113	0.0098	-0.0016	0.0102
Household head is a farmer (=1)	-0.0022	0.0090	0.0099	0.0113
Household asset index	0.0026	0.0022	0.0041	0.0032
Number of visits/contacts from extension officers	0.0011	0.0048	0.0080	0.0069
Number of visits/contacts to extension officer	-0.0013	0.0066	0.0039	0.0072
Rice subsidy (=1)	0.0265	0.0169	0.0137	0.0211
Experience with crop loss (=1)	0.0079	0.0142	0.0163	0.0211
ρ (Lagged Hybrid Rice Adoption)	0.6499***	0.0968	0.0299***	0.0069
λ (Lagged Errors)	-0.6672***	0.0736	0.1032***	0.0093
	N = 2612		N = 2612	
	R^2 = 0.188		0.221	

Note: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

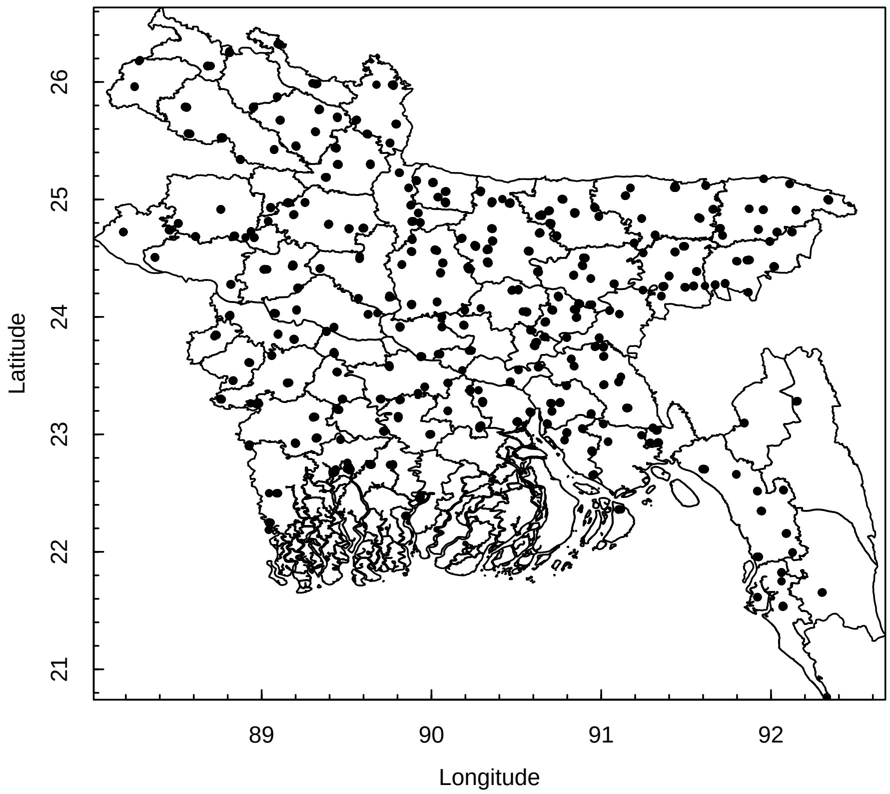

Figure 1: Geographic location of households in sample

Figure 2: Adoption of hybrid rice in Bangladesh (% of households)