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Capturing social network effects in technology adoption: the spatial diffusion of hybrid rice in Bangladesh*

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In this paper, we demonstrate a method for measuring the effect of spatial interactions on the use of hybrid rice using a unique, nationally representative data set from Bangladesh. In order to circumvent the 'reflection problem', we consider an identification and estimation strategy employing a generalised spatial two-stage least squares procedure with near-ideal instruments to effectively identify causal influences. Results indicate that neighbour effects are a significant determinant of hybrid rice use. Further, using two specifications of spatial network systems, one based on same-village membership (irrespective of distance) and the other based on geographical distance (irrespective of village boundary), we demonstrate that a network including nearby hybrid rice adopters is more influential than a network of more distant hybrid rice adopters, and merely having a network with a large number of adopters may be relatively meaningless if they are far away. Furthermore, we show that these network effects are much more important to hybrid cultivation than interactions with agricultural extension officers.

Key words: hybrid rice, social network, spatial diffusion, technology spillover.

1. Introduction

Despite the very high importance of rice as a component to Bangladeshi livelihoods, rice productivity growth has stagnated since the mid-1990s. There remains significant potential to increase overall rice production through the increased adoption of rice hybrids, many of which provide significant yield advantages over traditional and even modern high yielding varieties. Increasing the cultivation of hybrids has the potential to significantly benefit 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

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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 cultivation remains relatively low. As of 2009–10, only 6% per cent of total agricultural area was used to cultivate hybrid rice (Rashid *et al.* 2011; Spielman *et al.* 2012). Among other factors, information limitations, credit constraints, liquidity constraints, and supply side constraints remain significant barriers to the widespread uptake of hybrids. In addition, there are several characteristics of hybrid rice—both in general and specific to the Bangladeshi context—that complicate farmers' decision-making. First, hybrids often produce yields 15–30 per cent higher than modern varieties (Azad *et al.* 2008). In addition, because of hybrid vigour and uniformity, hybrids require a lower seeding rate than varieties, usually requiring 67 per cent less seed per acre. But the benefits of the hybridisation process (e.g. increases in the level and uniformity of yields) decline dramatically and eventually disappear in subsequent generations, due to the segregation of dominant and recessive alleles, restricting these benefits to first-generation seeds. To continually realise 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 varieties, even modern high yielding varieties. Farmers must weigh the benefits of increased yield and seed efficiency with the higher costs of seeds that must generally be purchased anew in subsequent seasons.

In this article, we examine spatial dimensions of hybrid rice cultivation. Focusing on spatial dimensions in technology diffusion has several advantages. First, it explicitly recognises that knowledge about new technologies spills over within members of spatially defined networks. Knowledge about such technologies tends to spill over within local networks because farmers in local networks tend to face similar conditions, have more direct interactions with one another and can directly observe the costs and benefits of new technologies with their own eyes rather than relying on hearsay. Second, because these knowledge spillovers result in feedback loops, there are multiplier effects that have important policy implications. Understanding how knowledge about new technologies is diffused through these networks allows for improved extension strategies, for example, targeting specific areas or communities or even individuals where or to whom technologies should be introduced to generate the widest impact. Third, spatial dimensions are often ignored in adoption studies, or rudimentary approximations for spatial effects are considered, and that may have consequences on the magnitude of estimated regression coefficients as well as their inference.

We utilise data drawn from a nationally representative household survey in Bangladesh to demonstrate that interactions within a spatial context (i.e. observations on hybrid rice cultivation from members of defined neighbourhood structures) are important determinants of hybrid rice diffusion. Our identification and estimation strategy attempts to overcome the 'reflection problem' by employing a generalised spatial two-stage least squares procedure that uses near-ideal instruments, allowing us to more effectively identify causal influences arising from network interactions. These near-ideal instruments include spatially lagged observations of exogenous explanatory regressors, under the assumption that the only effect of these spatially lagged variables on farmer hybrid cultivation is indirect, through their effect on neighbours' hybrid rice cultivation. By incorporating a spatial error component within our broader econometric specification, we are also able to control for correlations of unobservable characteristics which may condition behaviour. The resulting empirical framework allows for more effective decomposition of endogenous behavioural factors arising from social networks and other correlated effects that arise from members of the same neighbourhood group being exposed to the same unobservable influences.

2. Literature Review

There is a rich literature studying the process of technology adoption and diffusion.[1] 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 (e.g. Foster and Rosenzweig 1995; Duflo *et al*. 2006; Conley and Udry 2010). Throughout the sociological or psychological literature, there has long been a realisation that social or peer influences have a powerful effect on behaviours (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 realisations have persisted, there is not a clear consensus on the manner in which group membership influences behaviour.

Manski (1993) suggested three hypotheses to explain the effect of group membership on an individual's behaviour: endogenous effects, contextual effects and correlated effects. Endogenous effects reflect the fact that individual behaviour influences the average group behaviour while at the same time being influenced by group behaviour. Contextual effects reflect the fact that an individual's behaviour 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 use of a particular technology is largely influenced by the patterns of use among other farmers in his or her social network (e.g. family, village, cooperative group, etc.), but the farmer's

[1] Among the factors linked with adoption include tenurial arrangements (e.g. Bardhan 1979), farm size (e.g. Feder 1980), education (e.g. Foster and Rosenzweig 1996), credit constraints (e.g. Lipton 1976; Feder and Umali 1993; Dercon and Krishnan 1996), information constraints (e.g. Fischer and Lindner 1980), and risk (e.g. Sandmo 1971; Feder 1980; Feder *et al*. 1985; Liu 2013).

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 agricultural 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 use, but only affect technology use indirectly, through their disaggregated effect on individual behaviour, which then has direct endogenous effects.

The disentangling of the different 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 behaviour, for example, indirectly affect the behaviour of other members of his or her social network, which in turn subsequently affect the individual, and provide an avenue whereby investments can result in the self-sustaining 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 behaviours that policymakers can capitalise on.

It has long been thought that the dissemination of agricultural technologies through extension services is sufficient to guarantee widespread adoption among farmers. More recent evidence suggests that learning from one's own experiences and learning from the experiences of others represent significant channels through which technologies disseminate among farmers. Case (1992) shows that farmer's adoption of sickle in Indonesia for rice farming is dependent upon neighbouring 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. Similarly, Conley and Udry (2010) find in their study in Ghana that pineapple farmers adjust their inputs to align with those of their information neighbours who were successful in previous periods.

Social networks based on geography (i.e. homestead and plot locations), kinship, friendship or religion facilitate the dissemination of technologies through farmers. Knowledge spillovers and learning externalities may facilitate trust-building about the new technology. Foster and Rosenzweig (1995) show that farmers with experienced neighbours are significantly more profitable than those with inexperienced neighbours. Holloway *et al.* (2002) find a positive and significant neighbourhood effect on high yielding variety adoption in Bangladesh. Langyintuo and Mekuria (2008) find evidence not only that neighbours' adoption influences farmers' adoption, but also that membership in farmer associations and contact with extension officers positively affects adoption of improved maize adoption in Mozambique. Interactions and learning facilitate increased productivity growth by fostering the spread of improved technologies within social networks.

Even though the role of networks and knowledge spillovers is acknowledged in the literature, the econometric methodologies used for this investigation are quite diverse, and identification challenges can be daunting, often requiring strong assumptions (Manski 1993). 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 or simply contend to use rudimentary conventional proxies such as regional dummy variables, distances to urban or market centres to account for effects of spatial spillovers (Staal *et al*. 2002). 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. An endogenous effects model could take the form of spatial correlation models, with a simple two-stage estimation procedure used to estimate pure endogenous effects. Such a pure effect model, however, explicitly assumes the absence of spatial correlations among unobservable factors, which almost certainly play a significant role in conditioning technology choices.

3. Theory

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 discrete periods: farmers make input decisions in period t and realise output in period $t + 1$. Realised output (per unit of land) can be written

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

where $y_{i,t+1}$ is realised 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 v_t characterises growing conditions. Note that we have written equation (1) such that current growing conditions affect both the input response function as well as the exogenous, stochastic productivity shock. Farm profits can be written

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

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

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

Since $\varepsilon_{i,t+1}(v_t)$ is a mean-zero stochastic process, we have $E_{it}[f(x_{it;}v_t) + \varepsilon_{i,t+1}(v_t)] = E_{it}[f(x_{it;}v_t)]$. We assume that current expectations are a function of both one's own experiences (i.e. realised profits) as well as the experiences of other farmers within one's social network. Expected productivity can be written

$$E_{it}[f(x_{it}; v_t)] \in E_{it}[f(x_{it}; v_t)|\, Y_{it}(X_i),\, Y_{jt}(X_j), \gamma_t]\ \forall j \in J \tag{4}$$

In this identity, $Y_{it}(X_i) = y_{it}(x_{it;}v_t),\ y_{i,t\text{-}1}(x_{i,t+2}),\ldots,\ y_{i,t-T+1}(x_{i,t\text{-}T})$ summarises farmer i's memory in period t of his own input decisions and observed next-period output (to the extent of his memory, T); $Y_{jt}(X_j) = y_{jt}(x_{j,t\text{-}1}),\ y_{i,t-1}(x_{j,t-2}),\ldots,\ y_{j,t-T+1}(x_{i,t-T})$ summarises farmer i's memory in period t of the input decisions and observed next-period profits of neighbour $j \equiv J$, where J is the set of all members in farmer i's social network, and $\gamma = v_{t-1}, v_{t-2},\ldots, v_{t-T}$ reflects farmer i's memory in period t of past growing conditions (e.g. soil or weather). At time t, 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.[2] From solving the farmer's profit maximisation problem, we can write a reduced form hybrid rice use equation as

$$x_{it} = g(E_{it}(p_{t+1}),\, Y_{it}(X_i),\, Y_{jt}(X_j), \gamma_t, r_t; Z_{it}) \tag{5}$$

The Z_{it} terms demonstrate idiosyncratic differences that may lead to differences in hybrid adoption between otherwise observationally equivalent farmers. Given the presentation of equation (5) 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

[2] Let $E_{it_o}[f(x_{it;}v_t)|\,Y_{i,t-1}(X_i),\, Y_{j,t-1}(X_j), \gamma_{t-1}$ represent baseline prior expectations in period t before observing $Y_{it}(x_{i,t-1};\ v_{t\text{-}1})$ or $Y_{jt}(x_{j,t\text{-}1};\ v_{t-1})\ \forall\ j\ \in\ J$. Then, let $\Delta E_{it}[f(x_{it}; v_t)] \in E_{it}[f(x_{it}; v_t)|\,Y_{it}(X_i),\, Y_{jt}(X_j), \gamma_t] - E_{it_o}[f(x_{it}; v_t)|\,Y_{i,t-1}(X_i),\, Y_{j,t-1}(X_j), \gamma_{t-1}]$ 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 $E_{it}[f(x_{it};\ v_t)] \in E_{it}[f(x_{it};\ v_t)|\ Y_{jt}(X_j),\ \gamma_t]$, and $\Delta E_{\text{it}}[f(x_{\text{it}};v_{\text{t}})]$ will have the same sign as $\pi_{jt} = (x_{j,t-1};\, p_t,\, r_{t-1},\, v_{t-1}) < E_{ito}[\pi_{jt}(x_{j,t-1})]$ (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 $\Delta E_{it}[f(x_{it};\ v_t)] > 0$, even under cases where $\pi_{jt}(x_{j,t-1}; p_t, r_{t-1}, v_{t-1}) < E_{it_0}[\pi_{jt}(x_{j,t-1})]$. The converse is also possible. Additionally, we will assume that learning is local, so that $\Delta E_{it}[f(x_{it};\ v_t)]|\ Y_{it}(x_i),\ Y_{it}(X_i),\ \gamma_t = 0\ \forall\ l \in J$.

this exercise. The hybrid rice adoption decision can be modelled as the binary variable H_i such that

$$H_i = \begin{cases} 1 & \text{if } x_i > 0 \\ 0 & \text{Otherwise} \end{cases} \tag{6}$$

It is possible that households could have used hybrids in a previous season and chosen to cease cultivating hybrids for one reason or another. Due to data limitations, we do not have data on such disadoption, but we note that since hybrids are a relatively new phenomenon in Bangladesh, this should not be a significant concern for the majority of households.

4. Empirical Methods

Farmers' use of a technology is often modelled through a limited dependent variable econometric 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 technology use in a probabilistic setting: factors X affect the probability that technology y will be used. If social interactions facilitate technology use decisions, then an important explanatory variable included on the right hand side of any regression equation would be spatially lagged dependent variables: $\sum_{j \in J} \omega_{i,j} y_j$, where J captures i's network, $\omega_{i,j}$ represents the (i,j) element of a spatial weights matrix (satisfying standard assumptions), and y_j is the observation of y for network member $j \in J$.

Technology use among members of a group may be similar because group members have similar characteristics or because they are exposed to similar institutional environments. If these characteristics 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 correlation among unobservables has been shown to bias coefficient estimates (Ward *et al.* 2014). Several previous researchers have acknowledged the existence of such correlations affecting technology 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). We control for these correlations through spatially lagged errors. We specify our econometric model based on equations (5) and (6) as

$$\begin{aligned} H_i &= \alpha + \rho \sum_{j \in J} \omega_{ij} H_j + Z_i' \beta + \varepsilon_i \\ \varepsilon_i &= \lambda \sum_{j \in J} \omega_{ij} \varepsilon_j + u_i \end{aligned} \tag{7}$$

where H_k, $k = i,j$ is a binary hybrid rice use measurement corresponding to farmer i and network member j, z_i' is a vector of household characteristics, ε_i is a composite error term consisting of spatial correlations among unobservable characteristics with members of one's network (ε_j) and idiosyncratic random error terms (u_i), and $\omega_{i,j}$ is the (i, j) element of a spatial weights matrix defining the structure of the spatial setting, with $\omega_{ii} = 0$. The ρ and λ terms are spatial correlation coefficients corresponding to spatially lagged dependent variables and errors, respectively, with parameter space assumed to be $(-1,1)$. This model is a variant of the standard Cliff-Ord model (Cliff and Ord 1981), with the addition of a spatial process among unobservables. Using 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 modelling, we specify the binary dependent variable model as a linear probability model.

The first row of equation (7) implies that household i's hybrid rice use is a function of i's neighbours' use as well as i's exogenous characteristics. Variables included in z_i' 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 (7) captures spatial correlation in unobservable factors, also referred to as spatially lagged errors or spatial autoregressive errors. This term reflects the fact that farmers in the same network behave similarly because they are exposed to similar unobserved characteristics that condition cultivation decisions.

We specify our spatial system in two different fashions. In what follows, these 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. First, for W_1, we construct a system in which the strength of network relationships is inversely related to the physical distance (in kilometres) between households. In other words, $\omega_{ij}^1 = 1/f(d_{ij})$, where d_{ij} is the distance between network members i and j, and f is some function of the distances. In our specification, $\omega_{ij}^1 = 1/(d_{ij}^2)$. To maintain an invertible weights matrix, we first define a threshold band within which these inverse distance weights are applied. The sums $\sum_{j \in J} \omega_{ij}^1 H_j$ are the distance-weighted average rate of hybrid usage among the members of farmer i's network. 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 behaviour, regardless of the actual distance between them. Therefore, the sums $\sum_{j \in J} \omega_{ij}^1 H_j$ are simply the total number of hybrid rice adopting farmers in i's network.[3]

[3] For W_1, the average number of links is 24.05 with an average weight of 0.4, while the average number of links for W_2 is 12.61, each with a weight of 1. These matrices are very sparse matrices, with 0.9 per cent and 0.05 per cent nonzero elements, respectively.

Our identification of knowledge spillovers 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 generalised spatial two-stage least squares. We can rewrite equation (7) in matrix notation (for a sample of size N) as

$$\begin{aligned} H_N &= M_N \delta_N + \varepsilon_N \\ \varepsilon_N &= \lambda_N W_N \varepsilon_N + u_N \end{aligned} \tag{8}$$

with $M_N = [Z_N,\ W_N H_N]$ and $\delta_N = [\beta'_N, \rho_N]$. Kelejian and Prucha (2010) propose a two-step procedure for efficiently estimating all of the model parameters, with subprocedures in each step. In the first step, the model is estimated by two-stage least squares (2SLS) using the instruments Q_N (introduced below). The autoregressive parameter λ_N is estimated based on the 2SLS residuals using the generalised moment approach developed by 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 generalised spatial 2SLS (GS2SLS). The GS2SLS residuals are then used to obtain a consistent and efficient estimator for λ_N.

Consider the endogenous regressor $W_{\mathrm{N}}\ H_{\mathrm{N}}$. Note that so long as the eigenvalues of W_N are all less than one, $E(H_N) = (I_N + \rho_N W_N + \rho_N^2 W_N^2 +)\ Z_N \beta$. Then, an ideal instrument for $W_{\mathrm{N}}\, H_{\mathrm{N}}$ is $E(M_N) = [Z_N,\ W_N E(H_N)]$. Given that $E\,(H_N)$ is an infinite series, we can approximate for the ideal instrument using an $N \times p$ subset (Q_{N}) of the linearly independent columns of $E\,(M_N)$, such that $Q_N = [Z_N, W_N Z_N, W_N^2 Z_N^2]$. Then, we can write the projection matrix $P_{QN} = Q_N (Q'_N Q_N)^{-1} Q_N$. The first step 2SLS estimator for $\tilde{\delta}_N$ is

$$\tilde{\delta}_N = (\hat{M}'_N \hat{M}_N)^{-1} \hat{M}'_N H_N \tag{9}$$

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

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

$$H_N^*(\tilde{\lambda}_N) = M_N^*(\tilde{\lambda}_N)\delta_N + u_N$$

where $H_N^*(\tilde{\lambda}_N) = H_N - \tilde{\lambda}_N W_N H_N$ and $M_N^*(\tilde{\lambda}_N) = M_N - \tilde{\lambda}_N W_N M_N$; these variables have undergone a spatial Cochrane–Orcutt transformation, which can be achieved by simply premultiplying by $(I_N - \tilde{\lambda}_N W_N)$.

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

$$\tilde{\delta}_N(\tilde{\lambda}_N) = (M_N^*(\tilde{\lambda}_N)' M_N^*(\tilde{\lambda}_N))^{-1} M_N^*(\tilde{\lambda}_N)' H_N^*(\tilde{\lambda}_N) \tag{10}$$

The recomputed 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 use is through their effect on neighbours' use. 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 there are no contextual effects conditioning hybrid rice cultivation. While one might propose 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 cultivation of hybrid rice *except* insofar as higher average levels of education lead to higher average levels of hybrid rice cultivation in the network. So the causal chain runs from neighbours' higher levels of education to neighbours' higher rates of hybrid cultivation, which in turn leads to increased cultivation for the individual in question. We feel the assumption is justified and omit any cross-regressive terms that would capture these contextual effects.

5. 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 viewed as the most comprehensive nationally representative survey ever conducted in Bangladesh (Ahmed 2013). We restrict our sample to rice-growing households with a nonzero area of cultivated land, yielding a sample of 2612 households. The locations of households included in our sample are shown in Figure 1, while summary statistics for these data along with summary statistics for hybrid rice cultivation are presented in Table 1. As can be seen from Figure 1, the households in the sample are widely distributed throughout Bangladesh. We note from Table 2 that only about 10 per cent of households in the sample cultivate hybrid rice, suggesting significant scope for continued technological diffusion.

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 directly control for either households' or network members' previous experiences with hybrid rice. Specifically, we do not know whether the household has previously cultivated hybrid rice, nor do we know whether network members have done so. These experiences are bidirectional and recursive in nature: farmer i's past experiences influence his own current decisions, as well as the past and present decisions of his neighbour, farmer *j*. Similarly, farmer j's past experiences not only influence his own current decisions, but also the past and present decisions of farmer *i*. Both farmers' hybrid rice cultivation decisions would be conditioned by their own as well as

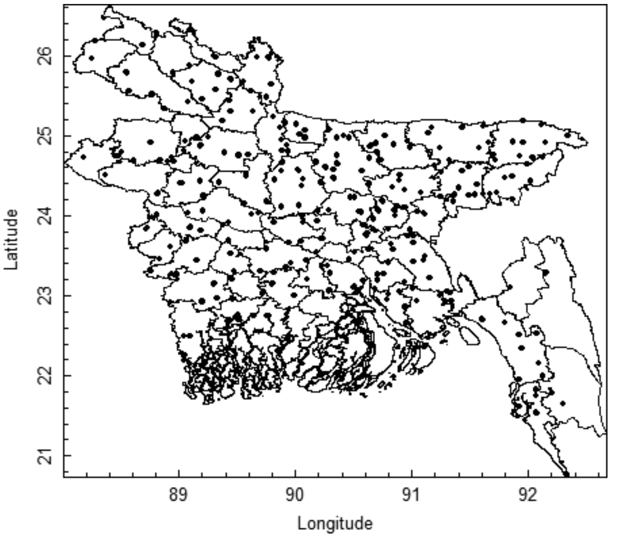

Figure 1 Geographical location of villages included in sample.

Table 1 Summary statistics of variables included in empirical analysis

Variables	Mean	Standard deviation	Minimum	Maximum
Hybrid adoption (=1)	0.095	0.293	0.000	1.000
Household head age (years)	45.513	13.397	18.000	95.000
Agricultural area (decimals)	0.664	0.706	0.004	9.014
Access to credit (=1)	0.834	0.372	0.000	1.000
External decision-makers (=1)	0.219	0.414	0.000	1.000
Dependency ratio (dependents/ economically active adults)	0.554	0.719	0.000	5.000
Migrants (number of persons)	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 (polychoric PCA)	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 officers	0.106	0.706	0.000	20.000
Rice subsidy (=1)	0.107	0.309	0.000	1.000
Crop losses in last 5 years (=1)	0.100	0.299	0.000	1.000

their neighbour's unobserved past experiences. These omitted variables would normally be subsumed into the disturbance terms and bias coefficient estimates, but we are able to control for the correlation between these unobservable effects through the addition of the spatial error process in our econometric specification. While we have suggested that the spatial error term captures the fact that farmers may behave similarly because they are exposed to the same environmental conditions, we also note that this reflects the fact that they are exposed to the same pool of combined experiences with respect to hybrid rice.

Table 2 IV/GMM Spatial ARAR(1,1) regression results

Coefficient	Inverse distance weights		Village binary weights	
	Estimate	Standard error	Estimate	Standard error
Household head age (years)	−0.0002	0.0002	−0.0003	0.0003
Agricultural area (decimals)	0.0287***	0.0082	0.0412***	0.0094
Access to credit (=1)	0.0224**	0.0098	0.0220*	0.0126
External decision-makers (=1)	0.0054	0.0112	0.0000	0.0143
Dependency ratio (dependents/ economically active adults)	−0.0076	0.0053	−0.0004	0.0066
Migrants (number of persons)	−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 (polychoric PCA)	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 officers	−0.0013	0.0066	0.0039	0.0072
Rice subsidy (=1)	0.0265	0.0142	0.0163	0.0211
Crop losses in last 5 years (=1)	0.0079	0.0142	0.0163	0.0211
(lagged hybrid rice adoption)	0.6499***	0.0968	0.0299***	0.0069
(lagged errors)	−0.6672***	0.0736	0.1032***	0.0093
N	2612		2612	
R^2	0.188		0.221	

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

Second, there are challenges in identifying networks. Any attempt at analysing social influences in behaviour must somehow define the social system, which is a nontrivial matter. The challenges associated with measuring and specifying social networks have become a topic of particular interest in recent years (Chandrasekhar and Lewis 2011; Maertens and Barrett 2012). Specification is particularly tricky with survey data. Even though the BIHS is nationally representative, it is still not the entire population and undoubtedly omits members that are potentially relevant in conditioning behaviour while simultaneously including those that may be irrelevant. We openly acknowledge this shortcoming, yet suggest that the representativeness of the data at least allow us more flexibility in observing aggregate network effects, though not direct individual effects.

Figure 2 illustrates the pattern of hybrid rice cultivation at the upazila level in Bangladesh. There certainly appear to be spatial patterns of hybrid rice cultivation, with high usage rates in the north-western Rajshahi and Rangpur divisions and the southeast Chittagong division, and low usage rates in the central division of Dhaka and the southern divisions of Barisal and Khulna. Forgoing potentially unrealistic assumptions of global stationarity, we compute local statistics to test for clustering or spatial correlation in hybrid rice cultivation. These local indicators of spatial association (Anselin 1995) indicate significant spatial relationships in the rates of hybrid rice cultivation

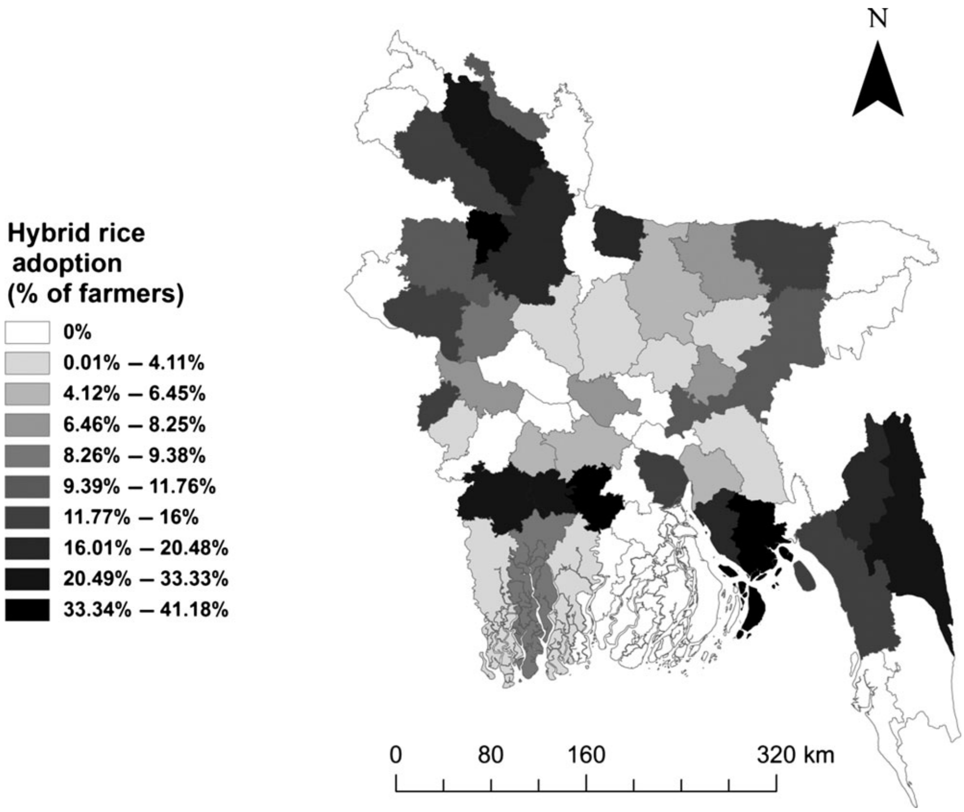

Figure 2 Adoption of hybrid rice in Bangladesh among BIHS households, by upazila.

in several districts, including Nilphamari and Rangpur districts in Rangpur division and Jaipurhut district in Rajshahi division.

To test for the conditional influence of social interactions at the household level, we introduce a series of explanatory variables assumed to impact household hybrid rice cultivation decisions. These household characteristics include the age of the household head; agricultural land area; access to credit; a variable capturing whether external parties are able to exert influence on agricultural decisions, including crop choice and input use; dependency ratio (share of dependents to working age household members); number of migrants in the household; literacy of household head; primary occupation of the household head; household assets; interactions with agricultural extension officers; experience of crop losses; and rice subsidy.[4]

[4] 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.

6. Results

Table 2 reports the results of estimating equation (7) by IV/GMM allowing for heteroskedasticity of an unknown form. These results reveal some interesting insights, particularly regarding neighbourhood influence on hybrid rice cultivation. The spatial lag parameter ρ is both positive and significant, regardless of the weights matrix specification. This confirms assumptions that there is significant spatial correlation in hybrid rice cultivation. The magnitude of the influence, however, 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 use. 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 behaviour than more distant network members. Recall that, in our specification $\omega_{ij}^1 = 1/d_{ij}^2$, where d_{ij} is the distance between network members i and j. The effects of two network members j and k on i's use of hybrid rice are such that $\omega_{ij}^1 H_j > \omega_{ik}^1 H_k$ for $d_{ij} < d_{ik}$. The Boolean weights matrix, on the other hand, equally weights network members, and $\sum_{j \in J} \omega_{ij}^2 H_j$ 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 $\sum_{j \in J} \omega_{ij}^1 H_j$, our results suggest the number of nearby hybrid rice farmers in one's network has a larger effect on hybrid rice cultivation than merely the total number of hybrid rice adopters in one's network. While our results suggest that equally weighting network members' influence on behaviour can capture social influences, such equal weighting may not be optimal. These results suggest 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 neighbours in terms of cultivation of hybrid rice, and this result is robust across different specifications.

Some other noteworthy findings arise from the results reported in Table 2. 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 cultivation. This result is contrary to the findings of Langyintuo and Mekuria (2008), who found a positive and significant effect of extension interactions among farmers in Mozambique. This robust result is particularly important, especially in the light of the positive and highly significant network effects that are observed. One interpretation is that 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, learning from the experience of peers still dominates farmers' decision to use technologies. This may arise due to more frequent interactions with network members or perhaps due to relative differences in trust, since farmers are more likely to trust those with whom they have more in common. Anecdotal evidence would suggest that farmers do not really trust extension officers, since they are infrequent visitors and members of a social hierarchy to which farmers in rural Bangladesh are often quite removed. Furthermore, it should be noted 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 officers emphasise the rice varieties (hybrid in this case) in their portfolio could be instrumental in farmers' decisions. In all, the combination of these results may suggest that extension efforts need not reach more farmers, so long as they successfully reach the key entry points that serve to catalyse information dissemination.

Access to credit and subsidies also appear as significant determinants of hybrid rice cultivation (the effect of rice subsidies is significant at the 11 per cent 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 subsidised seed proves beneficial in stimulating demand for these technologies.

7. Conclusion

In recent years, there has been a growing interest 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 endogenous 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 cultivation of hybrid rice using a unique, nationally representative data set from Bangladesh. Our methodology allows for the identification of social network effects by allowing a farmer's hybrid cultivation decision to be conditioned by the hybrid cultivation decisions of the members of his network members. Additionally, we control for correlated effects by controlling for correlations in unobservable factors that condition hybrid use. To overcome issues of endogeneity, our identification strategy relies on allowing spatially lagged hybrid cultivation to be conditioned by a matrix of spatially lagged exogenous explanatory variables. Using a generalised spatial two-stage least squares estimator, we have shown that neighbour effects are a significant determinant of hybrid rice use 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.

Our empirical results are based on specifying relationships based on geographical proximity, but our methodology could easily be applied where relationships are defined on any of a number of other criteria, such as kinship, friendship, religion or membership in similar associations. Our results suggest that differentiating (and weighting) relationships based on strength rather than treating all relationships equally is an important consideration when attempting to estimate the effects of network membership on something like technology use.

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