Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture
Author(s): Andrew D. Foster and Mark R. Rosenzweig
Source: *The Journal of Political Economy*, Vol. 103, No. 6 (Dec., 1995), pp. 1176-1209
Published by: The University of Chicago Press
Stable URL: http://www.jstor.org/stable/2138708
Accessed: 16/01/2011 09:28

Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture

Andrew D. Foster and Mark R. Rosenzweig

University of Pennsylvania

Household-level panel data from a nationally representative sample of rural Indian households describing the adoption and profitability of high-yielding seed varieties (HYVs) associated with the Green Revolution are used to test the implications of a model incorporating learning by doing and learning spillovers. The estimates indicate that (i) imperfect knowledge about the management of the new seeds was a significant barrier to adoption; (ii) this barrier diminished as farmer experience with the new technologies increased; (iii) own experience and neighbors' experience with HYVs significantly increased HYV profitability; and (iv) farmers do not fully incorporate the village returns to learning in making adoption decisions.

I. Introduction

That individuals learn from their peers, neighbors, or friends is an important public policy assumption that underpins, for example, public subsidies of schooling and has been hypothesized to be a significant source of economic growth (Romer 1986; Lucas 1993). Quantitative evidence on the importance of learning externalities, however, is not extensive. While there are studies reporting associations between the behaviors of individuals and their neighbors, these studies

The research in this paper is supported in part from grants from the National Institutes of Health (HD30907) and the National Science Foundation (SBR93-08405). We are grateful to the referee and to participants at seminars at Berkeley, Brown, Chicago, Chinese University of Hong Kong, Columbia, Département et Laboratoire d'Économie Théoretique et Appliquée, International Food Policy Research Institute, Michigan State, Northwestern, Princeton, Stanford, and University of Washington.

[*Journal of Political Economy,* 1995, vol. 103, no. 6]

may be wholly spurious in that they may be driven by common unobservables (Case 1991; Evans, Oates, and Schwab 1992), or they may reflect, if real, peer influences that do not entail learning. The principal feature that distinguishes external effects due to learning from those due to mere mimicking or social pressure is that an individual's productivity, not just his or her behavior, is affected by his or her neighbor's behavior.

Just as the most appropriate test of learning by doing requires the measurement of changes in productivity, or the rewards to productivity, that accrue from experience (see, e.g., Bahk and Gort 1993), the identification of learning from neighbors also requires information on productivity or its rewards in addition to measures of neighbors' characteristics or behavior relevant to productivity growth. It is not sufficient, however, to find that an individual's productivity is affected by a neighbor's behavior to confirm the existence of learning from neighbors. It is possible, for example, that social pressure—by which neighbors collectively induce an individual to behave in some way—can improve that individual's productivity without any learning on the part of the individual. To test for knowledge spillovers and learning externalities requires a more precise specification of the learning mechanisms and of the production technology.

In this paper, we incorporate learning by doing and learning from others in a modified target-input model of new technology (Wilson 1975; Jovanovic and Nyarko 1994). We use the model to establish and carry out tests for individual and external learning effects based on panel data describing farmer behavior and profitability at the onset of the "Green Revolution" period in India. This time period, when new agricultural technologies were first imported into India, is particularly useful for examination of hypotheses concerning learning: while prior to the introduction of new seeds farmers had been using essentially the same technology for decades, new opportunities for greater productivity arose at least in some areas of the country for the first time.

The modeling approach we take, which emphasizes the problem of deciphering the optimal management of a new technology, contrasts with the recent work by Besley and Case (1993, 1994) on learning spillovers in agriculture. In their model, estimated using data from one village in India, the technology adoption problem is one in which the profitability of adoption is uncertain and exogenous; farmers thus learn from experience about true profitability. In target-input models, what is unknown and stochastic is the best use of inputs under the new technology. There are two reasons we adopt this alternative approach. First, optimal input use appears empirically to be central to farmers' concerns in environments subject to technological change, and there appears to be some suggestive but direct evidence of learning about the best use of inputs from others. Table 1 reports the results from questions posed to farmers in Green Revolution areas, taken from three surveys carried out in two countries, on farmers' sources of information on fertilizer input use (two surveys) and on agricultural practices, the latter for farmers using new seed varieties. In the Indian surveys, it is interesting to note that the only questions on information pertained to input use; there were none on the profitability of seeds. In all these surveys, neighbors appear to be important sources of information about input use, as important as formal public information dissemination sources.[1]

A second reason we adopt the target-input model is that, in contrast to models with uncertain but exogenous profits, the profitability of any new technology grows over time as knowledge accumulates. It is thus possible to test directly for learning externalities in terms of productivity, rather than by inference from farmer adoption behavior. Moreover, while it is not necessary to assume away the additional exogenous stochastic elements to new-technology profitability that are emphasized in Besley and Case's framework in estimating the consequences for profitability of learning about optimal practices, doing so provides testable implications for farmer adoption behavior that are otherwise difficult to derive. In particular, we are able to derive tests of whether neighbor and own experience are perfect substitutes and whether there is efficient learning.

In Section II, we set out the basic model, deriving implications for the effects of own and neighbors' experience with new technologies on profitability and on the scale of the new technology used. In Section III the data are described and the estimation procedures discussed. Section IV presents the estimates of the profit functions and adoption decision rules. Evidence is first presented on the existence of spurious correlation of neighbor behavior and individual profitability in the cross section, which is evidently eliminated using the estimation procedures employed subsequently. The profit function estimates show that new-technology profitability increases significantly with increases in both own and neighbor new-technology experience in ways consistent with the learning model: the returns to experience of both types diminish rapidly over time and at the same pace. The estimates of the adoption decision equations also are consistent with learning from neighbors, but they reject a model in which the learning externalities are completely internalized. Section V presents dynamic simulations based on the estimates and calibrated from

[1] These answers do not indicate the importance of the information for either profitability or behavior.

TABLE 1

INFORMATION SOURCES OF FARMERS IN THREE SURVEYS

	India		Philippines:
Source	ARIS: Source of Information about Fertilizer Use*	REDS: Source of Information about Fertilizer Use†	Bukidnon: Most Important Source of Information about Cropping Practices‡
Friends and neighbors	30.4	42.5	41.6
Government agency	51.4	62.9	...
Local extension agent	...	35.0	0
Demonstration projects	3.2	...	50.0

SOURCE.—For India: ARIS: NCAER Additional Rural Income Survey, 1970–71 (national); farmers, population-weighted counts. REDS: NCAER Rural Economic Development Survey, 1981–82 (national); 186 villages with HYV use. For the Philippines: IFPRI Bukidnon Survey, 1986; 12 corn farmers using HYV seeds.

* Percentage reporting source among 17 mutually exclusive categories.

† Percentage reporting source among seven nonexclusive categories.

‡ Percentage reporting source among eight mutually exclusive categories.

the data that show the effects of differences in farm wealth (scale) of farmers and their neighbors on the pace and magnitude of new-technology adoption and on profits. These simulations show that the estimates predict the well-known adoption S-curve that has characterized new-technology adoption in agricultural environments (Feder, Just, and Zilberman 1985) and that, as a result of learning spillovers and nonexclusion, a poor farmer with richer neighbors will benefit more from the introduction of new varieties than a poor farmer with similarly poor neighbors. Section VI contains concluding remarks.

II. Theory

To establish a framework providing empirically implementable tests of the presence of learning from others in terms of both productivity and behavior, we use a modified version of the target-input model, which has been used to study information acquisition and its effects on the productivity of innovations (see, e.g., Wilson 1975; Jovanovic and Nyarko 1994). The basic features of this model are that (i) individuals deciding on input decisions each year know the technology of production up to a random "target" for input use that has both a systematic and an idiosyncratic component, (ii) payoffs are decreasing in the square of the distance between actual input use and the target, and (iii) ex post, each individual can observe what the target had been in each year and thus draw inferences about the systematic component of the target.

This model is particularly suitable for the study of Indian agriculture at the onset of the Green Revolution, when the newly available technology was in the form of high-yielding variety (HYV) rice and wheat seeds. A well-known feature of HYVs is that yields are sensitive to modern inputs such as chemical fertilizer and pesticides as well as traditional inputs such as water. Both over- and underuse of these inputs can reduce yields, with the optimal level of use being influenced by region- and year-specific variables such as the quality of the soil, temperature, and the level of rainfall and groundwater.[2] Because there is regional variation in optimal input use, countrywide guidelines may have limited value compared with local experience in raising yields. Finally, traditional varieties are generally less sensitive to the use of these inputs, and because farmers have substantial experience with these varieties, additional experience with these crops is unlikely to affect yields.

We modify the basic model to make it more applicable to the Indian agricultural context. In particular, not only does the model incorporate the possibility of learning from the experience of neighboring farmers, but (i) the scale of operation is endogenous and importantly influences the precision of new information; (ii) farmers can use two technologies, traditional and new, simultaneously; and (iii) farmers can engage in strategic behavior.[3] To measure scale and to capture variation in the suitability of land to HYVs, we divide up the farmer's land into parcels of arbitrary size (e.g., acres, hectares, and decimals).[4] The production technology and information restrictions are as follows: optimal or target-input use on each parcel of land i planted using the new seeds by farmer j in each period t, $\tilde{\theta}_{ijt}$, is given by

$$\tilde{\theta}_{ijt} = \theta^* + u_{ijt}, \tag{1}$$

where θ^* is the mean optimal use and u_{ijt} is an independently and identically distributed (i.i.d.) normal random variable with variance σ_u^2. We consider below the implications of contemporaneous spatial correlations in the target shocks. Farmers are assumed to know σ_u^2 and have priors over θ^* that are $N(\hat{\theta}_{j0}, \sigma_{\theta j0}^2)$. Yield per parcel using traditional varieties is η_a, but yield per parcel using HYVs varies according to the suitability of land to HYVs and to input use. The (per parcel) yield from HYV seeds on the ith most HYV-suitable parcel

[2] Indeed, experimental plot data describing seed yields for wheat in Uttar Pradesh, India, presented in Bliss and Stern (1982) suggest that the relationship between fertilizer use and output per acre conforms closely to a quadratic for both traditional and high-yielding varieties. These data also show that HYV output is considerably more sensitive than traditional output to fertilizer use and that optimal fertilizer use for HYV exceeds that for traditional seeds.

[3] Jovanovic and Nyarko (1994) consider a menu of technologies, but this generalization is not relevant to the setting we study.

[4] We introduce variation in the suitability of land to the adoption of HYVs in order to ensure an interior solution for the HYV decision rules.

for a farmer with A_j total parcels of land is given by

$$\eta_a + \eta_h - \eta_{ha}\frac{i}{A_j} - (\theta_{ijt} - \tilde{\theta}_{ijt})^2, \tag{2}$$

where θ_{ijt} denotes actual input use and η_{ha} reflects the loss associated with using less suitable land as more HYVs are used.

A. *Learning and Profit Growth*

It is easy to show that under the assumptions of the model, expected profits at time t are a function of the farmer's posterior distribution for θ_j^* at time t:

$$\pi_{jt} = \left(\eta_h - \eta_{ha}\frac{H_{jt}}{2A_j} - \sigma^2_{\theta jt} - \sigma^2_u\right)H_{jt} + \eta_a A_j + \mu_j + \epsilon_{pjt}, \tag{3}$$

where $E_t(\epsilon_{pjt}) = 0$, μ_j captures variation among farmers in the overall productivity of their land, and $\sigma^2_{\theta jt}$ represents the variance of farmer j's posterior distribution over θ_j^* at time t.[5]

At the end of the harvest, the set of true or ex post optimal input levels, $\tilde{\theta}_{ijt}$, for each of the farmer's parcels in that year becomes known.[6] The farmer can use this information to update his priors with regard to the expected optimal input use, θ^*. When the shocks are independent across space, the variance associated with this signal is σ^2_u/H_{jt}. Thus the precision of the signal, H_{jt}/σ^2_u, increases propor-

[5] It may be shown that

$$\epsilon_{pjt} = -\sum_{i=1}^{H_{jt}} (\hat{\theta}_{jt} - \theta^* - u_{ijt})^2 + H_{jt}(\sigma^2_{\theta jt} + \sigma^2_u).$$

Note also that for notational convenience we use a continuous approximation to write the quadratic HYV term as $\eta_{ha}H^2_{jt}/2A_j$ rather than $\eta_{ha}(H_{jt} + 1)H_{jt}/2A_j$. With a suitably small choice for area units, the error associated with this approximation falls to zero.

We have assumed for simplicity that the input is costless. If the input price were p, then the ex ante optimal $\theta = \theta_{jt} - (p/2)$ and profits would include additional terms in θ_{jt}. The exclusion of p has no consequences for the implications derived from the profit function relations in (3), derived below, but would complicate the decision rules for H. The reason is that an individual with a history of shocks signaling low expected target use will anticipate a higher return to HYVs than an otherwise identical individual whose experience suggests high target use. Although incorporating this effect would substantially complicate the theory, because θ_{jt} follows a random walk, it would have only minor implications for the empirical implementation given our use of fixed-effects methods.

[6] Note that the information generated by a parcel sown to HYVs is independent of the input decision. This implies that there is no return to input experimentation, i.e., conscious variation across plots in a given year in input use. This assumption simplifies the input decision, which depends only on current expected profits and the information structure.

tionately with the number of parcels on which the farmer plants new-technology seeds. If the parcel-specific $\tilde{\theta}_{ijt}$'s on land planted with the new-technology seeds by the farmer's neighbors are also revealed to the farmer, then the signal precision in that year for the farmer will also depend on the amount of the neighbor's HYV area. However, to allow for the possibility that information from neighboring farmers is more noisy than that from own cultivated area, we assume that for each parcel of neighbors' land cultivated with the new seeds, what is revealed is $\tilde{\theta}_{ijt} + \xi_{ijt}$, where the variance of neighbors' noise, σ_{ξ}^2, is also known.[7]

Given the stationarity in the distribution of the $\tilde{\theta}_{ijt}$'s, the time of information is irrelevant.[8] Assuming that farmer j has n neighbors, we may therefore use Bayesian updating to write

$$\sigma_{\theta jt}^2 = \frac{1}{\rho + \rho_o S_{jt} + \rho_v \bar{S}_{-jt}}, \tag{4}$$

where $\rho = 1/\sigma_{\theta 0}^2$ is the precision of the farmer's initial priors, $\rho_o = 1/\sigma_u^2$ is the precision of the information obtained from each parcel planted by j on his own farm, S_{jt} is the cumulative number of parcels planted by farmer j up to time t, and $\rho_v = n/(\sigma_u^2 + \sigma_k^2)$ is the precision of the information obtained from an increase in $\bar{S}_{-jt}$, the average of the cumulative experience of neighboring farmers.

There are three important restrictions on the profit effects of experience implied by this learning technology. First, increases in the cumulative number of the parcels planted in HYVs by farmer j up to time t and in the cumulative HYV parcels of j's neighbors raise the profitability of j's high-yielding varieties at time t. To see this, substitute (4) into the profit equation (3). This yields a conditional (on HYV use) profit function $\pi_{jt} = \pi(H_{jt}, S_{jt}, \bar{S}_{-jt}, A_j, \mu_j, \epsilon_{pij})$ such that

$$\frac{\partial \pi_{jt}}{\partial S_{jt}} = \frac{\rho_o}{(\rho + \rho_o S_{jt} + \rho_v \bar{S}_{-jt})^2} H_{jt} \tag{5}$$

and

$$\frac{\partial \pi_{jt}}{\partial \bar{S}_{-jt}} = \frac{\rho_v}{(\rho + \rho_o S_{jt} + \rho_v \bar{S}_{-jt})^2} H_{jt}. \tag{6}$$

Second, as seen from (5) and (6), the ratio of the profitability effects of cumulative experience—measured in HYV area—of farmer j and

[7] Note that since each neighboring farmer's choice of the ex ante optimal input reflects that farmer's history of target realizations, these actual neighbor inputs are sufficient statistics to farmer j for his neighbor's prior experience and could be used instead of the full history.

[8] We exclude the possibility that farmers tend to forget experience over time.

of his neighbors on farmer j's HYV profitability is a time-invariant constant, ρ_v/ρ_o. Finally, with nonzero use of HYVs, the returns per hectare to both own and neighbors' experience diminish over time and at the same rate:

$$\frac{\dfrac{\partial(\pi_{jt+1}/H_{jt+1})}{\partial S_{jt+1}}}{\dfrac{\partial(\pi_{jt}/H_{jt})}{\partial S_{jt}}} = \frac{\dfrac{\partial(\pi_{jt+1}/H_{jt+1})}{\partial \overline{S}_{-jt+1}}}{\dfrac{\partial(\pi_{jt}/H_{jt})}{\partial \overline{S}_{-jt}}} = \frac{(\rho + \rho_o S_{jt} + \rho_v \overline{S}_{-jt})^2}{(\rho + \rho_o S_{jt+1} + \rho_v \overline{S}_{-jt+1})^2} < 1. \quad (7)$$

So far, we have assumed that the information is perfectly correlated within parcels and perfectly uncorrelated across parcels, so that the precision of the information is proportional to the number of parcels. Similar implications of Bayesian learning arise even if there is a village-level shock to the optimal target in each year. If the year-specific common shock variance is σ_v^2, the variance of farmer j's posterior distribution at time t is then

$$\sigma_{\theta jt}^2 = \frac{1}{\rho + \sum_{x=1}^{t} \dfrac{1}{[1/(\rho_o H_{jx} + \rho_v \overline{H}_{-jx})] + \sigma_v^2}}, \quad (8)$$

which reduces to equation (4) when $\sigma_v^2 = 0$. We show in Appendix A that the predictions of positive and declining experience effects and the constancy of the ratio of own and neighbor experience effects are identical to those arising in the i.i.d. case, but in this case in terms of the year-specific marginal additions to experience rather than cumulative experience.

These implications of the learning-by-doing model with neighbor effects can be tested through estimation of the profit function conditional on HYV use. Estimates of this function provide direct evidence of learning in addition to establishing whether and by how much individuals learn from their neighbors' experience, ρ_v.[9] Note that if the only source of uncertainty were imperfect knowledge about the profitability of HYVs as in Besley and Case (1994), learning would not affect the growth of profits conditional on HYV use. However, in that case, shocks to profitability influence the adoption decision. This has implications for the appropriate method for estimating the profit function, as discussed below.

[9] Note that the value of ρ_v depends on both the number of neighbors and the relative precision of information obtained from their experience; however, one cannot distinguish a situation of many neighbors with imprecise information from one of few neighbors with precise information using estimates of the profit function.

B. Learning and Technology Adoption

In addition to affecting the structure of the profit function, the existence of learning by doing and learning from neighbors' experience with respect to input use also has implications for adoption, that is, the choice of the scale of H_{jt}. In particular, if each farmer wishes to maximize expected discounted profits, with δ the discount factor, then the (unconditional) problem faced by farmer j at time t is

$$V_{tj} = \max_{H_{jx}} E_t \sum_{x=t}^{T} \delta^{s-t} \pi(H_{jx}, S_{jx}, \mathbf{S}_{-jx}, A_j, \mu_j, \epsilon_{pjx}), \tag{9}$$

where $\mathbf{S}_{-jt}$ is the vector of experience for other farmers in j's village, and therefore we may write

$$\begin{aligned} V_{jt} = \max_{H_j} E_t \Bigg[\Bigg(\eta_h - \eta_{ha} \frac{H_j}{2A_j} - \sigma_u^2 - \frac{1}{\rho + \rho_o S_{jt} + \rho_v \overline{S}_{-jt}} \Bigg) H_j \\ + \eta_a A_j + \mu_j + \epsilon_{pjt} \Bigg] + \delta V_{jt+1}. \end{aligned} \tag{10}$$

As is evident in equations (9) and (10), the decisions made by each farmer depend on the past planting decisions of neighboring farmers and his expectations about planting decisions in the future. Therefore, those neighbor characteristics that predict their future planting decisions will enter into the decision rules of every farmer. For example, a farmer whose neighbors have characteristics that make it likely that they will experiment with HYVs may tend to curtail his own experimentation. The reason is that he can realize a higher short-term return from planting the traditional variety and then shifting to the HYV when there is sufficient experience from his neighbors to make adoption directly profitable.

To capture the influence of neighbor characteristics on farmer adoption and to obtain more precise insights into how adoption is affected by learning, it is necessary to characterize strategic behavior. In particular, we make use of the solution concept of a *Markov perfect* equilibrium.[10] This solution concept implies that choices of farmer j

[10] See Fudenberg and Tirole (1991). The key feature of a Markov perfect equilibrium is that choices can depend only on past behaviors to the extent that these behaviors influence the potential payoffs or choice sets of the players. Thus the only variables summarizing the history of play that influence the value function at time t are S_{jt} and $\mathbf{S}_{-jt}$ because past HYV use affects payoffs only through its effects on the subjective distribution of θ^* for each farmer. Note that this solution concept effectively rules out the use of multiperiod penalties that could in principle be used to support efficient HYV decision making from the perspective of the community. Besley and Case (1994) also use this solution concept.

as well as his neighbors at time t depend only on the experience and asset variables and that, conditional on these variables, choices of H_{jt} and $\mathbf{H}_{-jt}$ constitute a Nash equilibrium in each period.

The following first-order condition characterizes the internal solution choice of the number of parcels H_{jt} planted with the new seeds at time t by farmer j, conditional on the time t choices of his neighbors and the state variables (farm size and own and neighbors' experiences):

$$\eta_h - \eta_{ha}\frac{H_{jt}}{A_j} - \sigma_u^2 - \frac{1}{\rho + \rho_o S_{jt} + \rho_v \bar{S}_{-jt}} = \frac{\partial \pi_{jt}}{\partial H_{jt}} = -\delta \frac{\partial V_{t+1}}{\partial S_{jt}}. \quad (11)$$

Expression (11) indicates that the marginal contribution to profits of the last parcel planted with HYV seeds in any period t is optimally negative. Farmers will always use more than the within-period profit-maximizing amount of the new technology because of the future profit gains that accrue as a result of learning by doing.

Formal solution of this problem requires backward induction from the final period T. Analytic solutions for the HYV decision rule cannot easily be derived for $t < T$. However, given a value function at time $t + 1$ and the restrictions imposed by Markov perfection, equation (11) for a farmer and his n neighbors can be solved to obtain decision rules of the form

$$H_{jt} = h_t(S_{jt}, \mathbf{S}_{-jt}, A_j, A_{-j}). \quad (12)$$

Insight into the nature of decisions made prior to period T may be gained through the examination of partial derivatives of the HYV decision rules at time $T - 1$ with respect to the state variables evaluated at the symmetric equilibrium (e.g., $A_j = A$, $S_{jt} = S_t$, $H_{jt} = H_t$). The expressions, which are complex, are contained in Appendix B. However, the effects of neighbors' assets on a farmer's adoption decisions permit discrimination among three models of learning: (i) if there is no learning from neighbors ($\rho_v = 0$), there are no effects of neighbors' assets on any farmer's adoption decision; (ii) if a social planner decides on the planting decisions for all farmers or learning externalities are otherwise internalized, the effect of neighbors' average assets on the amount of area planted to HYV by any farmer with n neighbors should be n times the effect of his own assets and both effects should be positive; and (iii) if, as is assumed in the model, information externalities are not internalized, the effects of neighbors' assets that predict future plantings of HYV on a farmer's adoption of HYV can be negative, although the own effects must remain positive.

The negative effect of neighbors' characteristics on adoption will depend on whether the returns to experience are increasing or decreasing. Consider a village made up of two farmers. An increase in a farmer's assets increases adoption in period T and thus increases the returns to experience in that period. Thus given the amount of HYV planted by farmer A, an increase in the assets of his neighbor, B, will increase B's HYV area in period $T - 1$. An increase in HYV use by B in period $T - 1$ increases the precision of information available to A in period T. How this increase in precision for the behavior of farmer A affects the adoption decision depends on the sign of $\partial^2 V_{jT}/\partial S_{jT}^2$, that is, on whether the returns to experience for him in period T are increasing or decreasing in experience.[11] If they are increasing (decreasing), then this increased precision will increase (decrease) the HYV planted by A in $T - 1$. Thus if B's assets increase and there are decreasing returns to experience, A is given an increased incentive to free-ride on his neighbor's learning by decreasing his own learning. This incentive results in a negative effect of B's wealth on HYV use by A. By contrast, a positive effect of B's wealth will result if there are increasing returns to experience.

The model also yields implications for the relative magnitudes of the own and neighbors' experience effects that are testable. First, if own and neighbors' experience contain the same amount of information ($\rho_v = n\rho_o$), then a further restriction on behavior is implied:

$$\frac{\partial H_{jT-1}}{\partial \bar{S}_{-jT-1}} = \frac{\rho_v}{\rho_o}\frac{\partial H_{jT-1}}{\partial S_{jT-1}} = \frac{1}{n}\frac{\partial H_{jT-1}}{\partial S_{jT-1}}. \tag{13}$$

That is, the relative effect of neighbors' and own experience on the amount of HYV chosen in each period is constant across all periods and is identical to their relative contribution to profits, as in (5) and (6). If information is transmitted imperfectly ($\sigma_k^2 > 0$), then the relative magnitudes of the effects depend again on whether the value function in period T exhibits increasing or decreasing returns to experience. In particular, if the returns to experience are decreasing,

[11] It may be shown that

$$\frac{\partial^2 V_T}{\partial S_{jT}^2} = \frac{A_j}{\eta_{ah}}\left[2\frac{\rho_o^2}{(\rho + \rho_o S_{jT} + \rho_v \bar{S}_{-jT})^3} - \eta_h - \sigma_u^2\right].$$

Note that for small (large) S_{jT} the returns to experience are increasing (decreasing) in experience. Although greater experience decreases the returns to future experience given the choice of HYV area, it also increases the return to planting HYVs in that period, which in turn raises the returns to experience.

then

$$\frac{\partial H_{jT-1}}{\partial \overline{S}_{-jT-1}} < \frac{\rho_v}{\rho_o} \frac{\partial H_{jT-1}}{\partial S_{jT-1}}, \tag{14}$$

with the inequality reversed if the returns to experience are increasing. The reason that own and neighbors' experience can have different effects in the decision rule than they have in the profit function is that the value function for farmer j depends on the precision of his own information as well as the precision of his neighbors' information, whereas the profit function depends only on the precision of his own information. In the presence of imperfect information, experience by j will increase the precision of j's information more than it will increase the precision of his neighbors' information, whereas an increase in neighbors' experience will have the opposite effect. If information is transmitted perfectly, then these two measures of precision coincide and thus equation (13) holds.

III. Data and Empirical Implementation

A. Data

The data that we use come from a panel data set from India, the National Council of Applied Economic Research (NCAER) Additional Rural Incomes Survey (ARIS), which describes rural households from a national probability survey begun in the crop year 1968–69, soon after the onset of the Indian Green Revolution when new HYV seeds first became available. The panel data set provides longitudinal information for 4,118 households pertaining to the crop years 1968–69, 1969–70, and 1970–71 on the area planted with the new high-yielding seed varieties (for wheat and rice), schooling, farm profits, and asset stocks and additions. An important feature of these data is that the 250 villages in which the households reside are identified. It is thus possible to construct village-level aggregates, based on sampling weights, that are representative of village inhabitants and have sufficient variation to test hypotheses about the influence of neighbors' characteristics and behavior. Both the extensive coverage and the longitudinal feature of the data set, as discussed below, are important for identifying cross-household learning effects.

Approximately two-thirds of the households interviewed in 1970–71, those in which the household head had remained the same up through 1981, were resurveyed by NCAER in 1981–82 (the Rural Economic and Demography Survey). While the data from this more recent panel round do not provide information on the use of HYV seeds or, more relevant to that period, on the vintages of the seeds used, information is provided on the assets inherited by the household heads prior to the 1968 round of the survey. This information will be used to construct instruments, as described below, for use with the earlier panel data set.

The ARIS data show that farmers' adoption of HYVs was rapid and occurred at an accelerated rate over the initial 3-year period: among farmers in villages in which at least one farmer cultivated with HYV seeds by 1970, only 19 percent were using HYV seeds in 1968, 29 percent had used the new seeds by 1969, and 42 percent had used them by 1970.[12] Among the farmers using HYV seeds in the 1970–71 crop year, HYV acreage had also increased at an accelerated pace, rising from only 4 percent of their cultivated acreage in the 1968–69 crop year and 3 percent of their acreage in the crop year 1969–70 to over 20 percent of their acreage in 1970–71.[13]

B. *Specification of the Profit Function*

The specification of the conditional profit function is obtained by substituting (4) into (3). We also incorporate the possibility that a farmer's schooling may also improve productivity of the new technologies, in accord with the hypothesis of Schultz (1975) that schooling is particularly useful in decoding information in a situation of "disequilibrium":

$$\pi_{jt} = \left(\eta_h - \sigma_u^2 - \eta_{ha}\frac{H_{jt}}{2A_j} - \frac{1}{\rho + \rho_o S_{jt} + \rho_v \bar{S}_{-jt}} + \eta_{he}E_j\right)H_{jt} + \eta_a A_{jt} + \mu_j + \epsilon_{pjt}, \tag{15}$$

where ϵ_{pjt} is the stochastic shock reflecting, among other things, the differences between the realized optimal $\tilde{\theta}_{ijt}$'s and actual input choices θ_{ijt}.[14]

[12] In these villages, 80 percent of the cultivators were growing either wheat or rice.

[13] The 1968–69 crop year was marked by extremely poor weather. This evidently had an effect on the following year's planting decisions. The possibility of prior weather shocks influencing HYV choice, although not explicitly modeled, is taken into account by the estimation procedure we use, as described below.

[14] Note that eq. (15) and the linear approximation derived from it (eq. [16]) assume i.i.d. shocks. Incorporation of village-level common shocks (eq. [8]) would require that separate coefficients in the linear approximation appear on each of the components of S_{jt}, i.e., $H_{j1}, \ldots, H_{jt-1}$. In principle, this result might be used to distinguish the two models. However, with only three years of HYV data and thus only two years over which experience effects can be estimated, the two models cannot be distinguished using linear methods. The reason is that the differenced linear approximation given village-level shocks that is analogous to eq. (16) has essentially the same specification; i.e., it includes cumulative own and neighbors' experience for each of the previous two years and yields the same predictions with regard to the ratios of these coefficients.

We use two different approaches to estimate equation (15). First, we estimate a linear approximation to the HYV profitability term in (15) and use this approximation to test the broad implications of the model. Then we take the exact specification of the profit function in the model entirely seriously in order to obtain structural estimates of the parameters. The linear approximation may be written as

$$\pi_{jt} \approx (\eta_h' + \beta_{ot} S_{jt} + \beta_{vt} \overline{S}_{-jt} + \eta_{he} E_j) H_{jt} + \eta_a' A_{jt} + \mu_j + \epsilon_{pjt}, \quad (16)$$

where η_h' and η_{ao}' are coefficients on H_{it} and A_{it}, respectively, and, to first order, $\beta_{ot} = \rho_o/[\rho + (\rho_o + \rho_v)S_t]$ and $\beta_{vt} = \rho_v/[\rho + (\rho_o + \rho_v)S_t]$ for some S_t that is representative of average experience at time t. The information coefficients, β_{ot} and β_{vt}, for own and village experience, respectively, embody the implications of the model; they thus should fall over time because experience is cumulative and, from (5) and (6), the ratio

$$\frac{\beta_{ot}}{\beta_{ot+1}} = \frac{\beta_{vt}}{\beta_{vt+1}} = \lambda_{pt} \quad (17)$$

is a time-specific constant, λ_{pt}.

We have specified the profit function (2), and its representation (15), to include a fixed effect μ_j. Because there is no asset accumulation in the model, the fixed effect does not influence the HYV decision net of assets. With assets endogenous, investment decisions and HYV choices are influenced by the unmeasured fixed effect, and equation (16) cannot be estimated using ordinary least squares (OLS) applied to cross-sectional data. For example, farmers who are persistently more profitable because they live in areas with better land will tend to accumulate more assets inclusive of land. This gives them a greater incentive to gain experience with HYVs since the returns to HYVs are increasing in land (eq. [15]) and will thus affect their and their neighbors' HYV use (eq. [12]). This will lead to a positive and spurious relationship between own profits and own and neighbors' prior HYV use.

We can exploit the panel characteristic of the data both to discern whether there are spurious relationships and to correct them. Differencing (16) over two points in time yields

$$\begin{aligned} \Delta\pi_{jt} \approx\ & \eta_h' \Delta H_{jt} + \beta_{ot+1} S_{jt+1} H_{jt+1} + \beta_{vt+1} \overline{S}_{-jt+1} H_{jt+1} \\ & - \beta_{ot} S_{it} H_{it} - \beta_{vt} \overline{S}_{-jt} H_{jt} + \eta_{he} E_j \Delta H_{jt} + \eta_a' \Delta A_{jt} + \Delta\epsilon_{pjt}, \end{aligned} \quad (18)$$

which removes the fixed effect. Note that there are now four coefficients associated with the experience variables in the differenced form of (16) because the model implies that both the experience coefficients and the variables vary over time. In particular, the experience coefficients, which reflect the profitability of additional experience, diminish whereas experience increases over time.

In the context of the model, OLS estimation of (18) would yield unbiased coefficients, since the compound error terms associated with the differences in the period-specific discrepancies between the choices of θ and their realizations $\tilde{\theta}_{ijt}$ cannot be correlated with any of the right-hand-side variables, given the independence of input-target shocks across time: H_{jt} is chosen prior to any knowledge about the $\tilde{\theta}_{ijt}$'s. It is possible, however, that the differenced profit shocks ($\Delta\epsilon_{pjt}$) may be correlated with the differenced HYV area measures. First, if some component of the shock is known prior to planting, then there will be a contemporaneous correlation between profit shocks and planting decisions. Second, lagged profit shocks may affect contemporaneous HYV use. For example, if the returns to HYV, net of the optimal input and observed weather shocks, are uncertain, as in Besley and Case (1993, 1994), lagged profit shocks affect profit expectations and therefore contemporaneous adoption.[15] This problem may be addressed using instrumental variables applied to (18): instrumental variables fixed effects. Given the removal of the fixed effect, the inheritance data may serve as instruments, and if all the shocks are independently distributed over time, decisions made before the resolution of the ϵ_{pjt} such as ΔA_{jt-1} and H_{jt-1} may serve as instruments as well.[16]

In addition to using standard instrumental variables fixed-effects methods to estimate equation (16), we implement a constrained fixed-effects approach that imposes and tests the equality of coefficient ratios for the experience variables (eq. [17]). Finally, nonlinear instrumental variables fixed-effects methods are used to directly estimate the structural parameters of equation (15) by differencing over time and then using a standard nonlinear instrumental variables procedure.

C. *HYV Cultivation*

Estimation of the HYV decision rule proceeds in essentially the same way as that for the linear approximation to the profit function. In particular, the analogue to equation (18) is thus

[15] In addition, the existence of borrowing constraints creates a correlation between contemporaneous HYV decisions and past input and weather shocks. Moreover, if capital accumulation is allowed and is also credit-constrained, then A_{jt+1} and $\Delta\epsilon_{pjt}$ will also be correlated.

[16] We exclude the use of H_{jt} as an instrument because some component of the profit shock (e.g., the timing of the monsoon) may be known at the time H_{jt} is chosen.

$$\Delta H_{jt} \approx \alpha_{ot+1} S_{jt+1} + \alpha_{vt+1} \overline{S}_{-jt+1} - \alpha_{ot} S_{jt} - \alpha_{vt} \overline{S}_{-jt} + \gamma_t \Delta t + \gamma_{ao} \Delta A_{jt} + \gamma_{av} \Delta \overline{A}_{-jt} + \Delta \epsilon_{hjt}, \tag{19}$$

which includes information on village average HYV experience and asset changes in addition to own experience and asset changes. Because the HYV decision rule is likely to have a time-specific component (e.g., given learning, HYV decisions will depend on the horizon over which the farmer is discounting), a linear time trend belongs in the linear level equation, and thus Δt appears in equation (19). Note that because we have not actually solved out for the decision rule, we cannot obtain measures of structural parameters using the decision rule estimates as in the case of the profit function. However, as noted, the magnitudes and signs of the estimated coefficients can be used to distinguish whether there is autarchy (neighbors' experience should not influence adoption, so that the $\alpha_v = 0$), whether own and neighbors' experience are equivalent (the relative effects of own and neighbors' experience are the same over time and as in the profit function), and whether there is strategic behavior in the form of free-rider effects (neighbors' assets decrease own use so that $\gamma_{av} < 0$).

IV. Results

A. *Profit Function Estimates and Spurious Village Effects*

To obtain the estimates of the conditional profit function (eq. [15]), we differenced the last two rounds of the three rounds of data for all farmers cultivating with HYV seeds in both of those rounds and applied instrumental variables estimation.[17] The own HYV experience variables include lagged cumulative HYV use by year for each farmer, measured in hectares, based on information from the first two rounds of the survey. The neighbor HYV experience variables include the lagged, round-specific cumulative sum of hectares cultivated under HYV averaged (using sample weights) over all sampled farmers in each village, whether or not they used HYV in any period, excluding the respondent farmer.[18] We use as measures of the poten-

[17] All these farmers grew wheat or rice in the 1970–71 crop year, for which we have crop data. Of these farmers, 70 percent grew wheat, with almost half of the wheat-growing farmers also growing rice. The data do not provide crop-specific profit and input information.

[18] As a result of differences in agroclimatic conditions, there was substantial variability across India in the suitability of HYVs during the initial stages of the Green Revolution. Because our model implies that HYVs will be used only when, under optimal use, they are more profitable than traditional varieties, we limit our analysis to villages in which at least one household used HYVs in the third year of the study (1970–

tial scale of operation, A_{jt}, variables that would be expected to augment the intensity of cultivation. They include the values of farm equipment, farm animals, and farm irrigation assets, which varied across rounds. Land owned and schooling did not change between rounds for any farmers and thus do not appear in the differenced equation.

As a specification test and a check on the ability of the differencing and instrumental estimation procedures to eliminate (and not cause) any spurious correlation of village (minus respondent) and individual variables, we first estimated the profit function for farmers *not* planting HYV seeds, using only the third-round cross-sectional data. For such farmers, the prior HYV acreage and experience of their neighbors using HYV seeds should be irrelevant to profitability, on the basis of traditional cultivation, whatever the true model underlying the transfer of knowledge of new technologies. If, however, high-profit areas are also areas in which farmers tend (not) to adopt HYV seeds, then it is possible to find a purely spurious positive (negative) correlation between past HYV use among village neighbor farmers and the profitability of non-HYV-using farmers. Column 1 of table 2 reports the cross-sectional estimates of the profit function based on the sample of traditional-technology farmers. The positive and (marginally) significant coefficient for the village-level HYV experience variable suggests the importance of area-specific unobservables: farmers who are not using HYV seeds apparently benefit from having neighbors with HYV experience. And, indeed, consistent with the proposition that this result is completely spurious, use of the fixed-effects procedure eliminates the association between the village-level variable and farmer-specific profits: in column 2, estimates of the differenced profit function (fixed effects) are presented, on the same sample of farmers, but they exclude any who had cultivated with HYV seeds in the second year. With the fixed effect removed, the relationship between neighbor HYV experience and the profitability of traditional seeds is no longer positive nor significant. Finally, columns 3 and 4 report estimates using the fixed-effects instrumental variables procedure based on the same sample as in column 1, column 4 including as well the prior-period experience variable suggested by the model. The use of instruments, while affecting the coefficients on the asset variables, does not substantially affect the estimated coefficient for the village experience variable estimated using fixed effects alone.

The results in table 2 suggest that, on the basis of the fixed-effects

71). Thus 101 of the 250 villages are included in our analyses. Village-level variables reflect the characteristics of all cultivating households, whether or not they use HYVs.

TABLE 2

CROSS-SECTIONAL AND PANEL ESTIMATES OF PROFIT FUNCTION FOR FARMERS NOT USING HYVs

	OLS (N = 1,536)	FIXED EFFECTS (N = 1,277)	INSTRUMENTAL VARIABLES FIXED EFFECTS (N = 1,277)	
	(1)	(2)	(3)	(4)
Village experience	.137	−.187	−.246	−.240
	(1.84)	(.654)	(.804)	(.784)
Initial period village experience				.166
				(.514)
Equipment	.085	.597	2.94	2.90
	(1.29)	(2.11)	(2.90)	(2.85)
Irrigation assets	.162	.050	.425	.440
	(7.68)	(.691)	(2.00)	(2.06)
Animals	.657	−.377	−1.74	−1.76
	(17.9)	(2.30)	(4.16)	(4.20)
Primary schooling ($\times 10^2$)	1.77	...	...	...
	(2.01)			
Irrigated land	.018	...	...	...
	(7.01)			
Unirrigated land	.032	...	...	...
	(9.34)			
House	.026	...	...	...
	(3.41)			

NOTE.—All variables are treated as endogenous for instrumental variables, fixed-effect estimates. Instruments include inherited assets, lagged asset flows, lagged profits, lagged village HYV use, and weighted averages of these variables by village. Absolute asymptotic t-ratios derived from Huber standard errors are in parentheses.

instrumental variables estimates, there is no positive relationship between the profits of traditional farmers and the experience of their neighbors with the new-technology seeds. If there is learning from neighbors, such experience should be relevant, however, for farmers using the new seeds. The HYV-conditional profit estimates (eq. [15]) for the sample of farmers using HYV seeds are presented in table 3. In the estimates in column 1, which assume that there are no village-level effects of experience, there is evidence of learning by doing: both the β_{ot} and β_{ot-1} coefficients, which reflect the effect of the farmer's own experience with HYVs on the current return to HYV cultivation, are positive and statistically significant. Moreover, as predicted by the model, the returns to experience diminish over time. The average area under HYV cultivation for an HYV-using farmer in the second period was 0.12 hectare; the coefficient for own experience in period 2 (β_{ot-1}) of .754 thus implies that a doubling of experience (from 0.1 to 0.2 hectare) in that period would result in a 905-rupee or 21 percent increase in mean profits. The coefficient for

TABLE 3

DETERMINANTS OF FARM PROFITS FROM HYV USE (N = 450)

	LINEAR APPROXIMATION			STRUCTURAL ESTIMATES:
	Instrumental Variables Fixed Effects		Constrained Instrumental Variables Fixed Effects	Nonlinear Instrumental Variables Fixed Effects
HYV EFFECTS	(1)	(2)	(3)	(4)
β_{ot} ($\times$ 10^5)	.170	.293	.187	. . .
	(2.13)	(2.54)	(1.88)	
β_{ot-1} ($\times$ 10^5)	.754	1.05	. . .	. . .
	(2.47)	(2.18)		
β_{vt} ($\times$ 10^5)	. . .	.349	.341	. . .
		(2.16)	(2.63)	
β_{vt-1} ($\times$ 10^5)	. . .	1.93	. . .	. . .
		(2.64)		
λ_{pt}	. . .	. . .	4.33	. . .
			(10.6)	
ρ_o ($\times$ 10^{-3})	. . .	. . .	. . .	1.29
				(3.31)
ρ_v ($\times$ 10^{-3})	. . .	. . .	. . .	3.46
				(1.33)
ρ ($\times$ 10^{-3})	. . .	. . .	. . .	.298
				(6.23)
η_{ha} ($\times$ 10^4)	. . .	. . .	. . .	−.290
				(3.24)
$\eta_h - \sigma_u^2$ ($\times$ 10^4)	. . .	. . .	. . .	.139
				(.77)
η_h' ($\times$ 10^4)	−.206	−.545	−.344	. . .
	(1.17)	(2.50)	(1.73)	
η_{he} ($\times$ 10^4)	.276	.434	.298	.610
	(1.22)	(1.91)	(1.34)	(3.54)
Farm equipment	2.25	2.64	2.55	1.67
	(2.98)	(2.59)	(2.68)	(2.73)
Farm animals	.641	.813	.543	.189
	(.57)	(.68)	(.49)	(.207)
Irrigation assets	−1.06	−1.17	−.693	−1.40
	(2.39)	(2.41)	(1.39)	(3.35)

NOTE.—HYV use is measured in hectares and asset values in rupees. All variables except education and Indian Agricultural Development Program (IADP) are treated as endogenous. Instruments include inherited assets, lagged asset flows, lagged profits, lagged village HYV use, and weighted averages of these variables by village. Absolute asymptotic t-ratios derived from Huber standard errors are in parentheses.

period 3 is substantially smaller as predicted by the model; however, the fact that by the third year the average cumulative area already cultivated under HYV was 0.12 hectare and average HYV area cultivated in the third year was 0.43 hectare implies that a doubling of HYV experience in the third period would increase profits by approximately the same magnitude (938 rupees or 22 percent).

The estimates from the specification allowing for both own and village-level experience effects are reported in column 2 of table 3.

The estimated effects on HYV profitability from increases in the experience of the village farmers, when own experience and the fixed effect are controlled for, are consistent with the hypothesis of learning from others: like the own experience effects, they are positive and significant and diminish over time. The own estimates suggest that a doubling of own experience in each of these periods results in a 39 percent and 36 percent increase in profits, respectively. It is interesting that the village experience effects on HYV profitability are similar in magnitude to the own effects, with the ratio of the two coefficients (and thus an indirect estimate of ρ_v/ρ_o) being 1.2 and 1.8 for periods 2 and 3, respectively. Thus either households make use of information from only a couple of neighbors (n is small) or if the experience of many neighbors is used by a farmer, the value of experience on others' farms is considerably less than the value of own experience.

Inclusion of the neighbor experience variables increased the size of the estimated effect of own experience in both periods 2 and 3 compared with the estimates in column 1. This suggests that, net of individual (and therefore village) fixed effects, own and village experience are negatively correlated. This result is consistent with the notion that certain characteristics may have opposite effects on own and neighbors' usage, a result that will be readily apparent below.

An important implication of the learning model is that, although the relative contributions to new-technology profitability of own and neighbors' experience may differ in each period, the diminution in the profitability of HYVs from additional experience should be the same for own and neighbors' experience. A test of this hypothesis (which is nonlinear in the estimated coefficients) was carried out and not rejected ($p = .11$). To obtain a more precise estimate of the decline in the returns to experience, we thus estimated a third model that imposes this constraint. The nonlinear constrained estimates are presented in column 3. They provide a direct estimate of the λ_{pt} ratio in (17) for both own and neighbors' experience across the second and third years. The point estimate is 4.33, suggesting that the effects of experience with the new technology on the profitability of the new technology fell rapidly over time as more experience was acquired.

The other coefficients for the first three models are broadly similar across specifications; we focus attention on the statistically and theoretically preferred estimates in column 3. The coefficients measuring the profitability of HYV seeds relative to traditional seeds, although they are not precisely measured in the third specification, suggest that such seeds were not profitable for a totally inexperienced farmer with no experienced neighbors. The point estimate of η_h', which measures the relative profitability of HYVs for an uneducated person with no experience, suggests that for each additional 0.1 hectare of HYVs planted in the first period there would be a loss in profits of 344 rupees (14 percent of average profits for uneducated farmers in that period). The positive value of η_{he} indicates that inexperienced educated farmers would lose considerably less: only 46 rupees.

The other model coefficients appear to be reasonable. The effects of equipment and animals on profitability are positive, with the former being strongly significant. The negative (but insignificant in the preferred specification) effect of irrigation assets is surprising, but it is worth noting that the average of the asset coefficients, which measures the average effect of an additional rupee of asset stocks on annual profits, is .80, which is significantly different from zero (p = .03).

Given that the linear models yield conclusions that are broadly consistent with the specific structure of the profit function that was assumed in Section I, we used nonlinear instrumental variables fixed effects to estimate the exact specification of the profit function (15). The structural estimates of the precision of the farmers' priors on input use in the initial new-technology period, ρ, the precision of the information obtained from an additional acre of own and neighbors' cultivation of HYVs, ρ_o and ρ_v, and the effect on profits from using less suitable land, η_{ha}, are presented in column 4 of table 3. The estimates, as expected, indicate that own experience, neighbors' experience, and better initial priors increase the precision of knowledge about the appropriate choice of the target input θ and thus increase profitability. The estimate of ρ_o indicates that each additional hectare of own experience results in an increase in precision of .00129. The ratio $\rho_v/\rho_o = 2.7$ measures the relative precision of information from own and neighbors' experience, which is only slightly larger than the figure obtained from the linear approximation estimates, although in this case the village-level effect is not precisely measured. Similarly, the ratio $\rho/\rho_o = .23$ measures the precision of the farmers' initial priors relative to the precision of each hectare planted and suggests that the precision of the priors held by the farmers prior to any experience with the new seeds was equivalent to what could be gained by planting 0.23 hectare of HYV. This is less than the average amount of information gained from own and neighbors' experience in the first year (0.37 hectare).[19]

[19] The other estimated profit function parameters are well behaved: the coefficient on the parameter estimate that captures the diminishing suitability to HYV adoption of land, η_{ha}, is negative and significant, as expected, and that for the level coefficient, $\eta_h - \sigma_u^2$, is positive.

B. Determinants of HYV Use

The fixed-effects, instrumental variables estimates of the HYVconditional profit function indicate that there is both learning by doing and learning from what others do. Estimates of the HYV decision rule (12) indicate whether own and neighbors' experience and predicted experience influence HYV adoption in a way that is consistent with the learning model. These estimates are presented in table 4. The estimates in column 1, based on a specification in which village-level experience effects are excluded, indicate that, consistent with the model and with the fixed effect controlled for, farmers having more prior experience with HYV seeds tend to use more of the new seeds in the current period. The point estimates, which are statistically significant, suggest that in year 2, an increase in prior experience from 0.1 hectare of HYV cultivation to 0.2 would have resulted in an 0.08-hectare (68.5 percent) increase in HYV use in that period. The effect in year 3 is larger, with the same increase in experience resulting in a 0.098-hectare increase, although the higher average HYV use in that period means that the percentage increase would be smaller (22.6 percent). The fact that the experience effect on the use of HYV does not fall over time, even though the contemporaneous profitability effects of experience diminish over time, is not surprising: in contrast to the case of the HYV-conditional profit function, the model does not yield clear predictions about how experience effects on adoption will change over time. Experience effects on adoption may increase over time, for example, if the effects of experience on the cost of learning (i.e., the cost of planting more HYV than would be dictated by equating the marginal profitability of HYV and traditional crops) dominate those arising from the diminishing returns to experience given adoption.

The inclusion of the neighbor experience and asset variables, reported in column 2 of table 4, results in a reduction in the coefficients on own experience, although these effects are still positive and significant. Although neither village-level experience coefficient is precisely measured, both effects are positive, as expected. It is interesting that the set of own and neighbor experience coefficients is consistent with the hypothesis that neighbors' and own acres are equally valuable in augmenting information (13), since the change over time in the effects of each type of experience is the same statistically (p = .165). This constraint is imposed, for efficiency, in the final specification, the estimates from which are reported in column 3. In this specification, the coefficients on the own and village-level experience variables are both significantly different from zero. For the HYV decision rule, the estimated ratio of period 2 to period 3 effects, λ_{ht}, is .78 < 1,

TABLE 4

DETERMINANTS OF HYV USE (N = 2,716)

	Instrumental Variables Fixed Effects (1)	Instrumental Variables Fixed Effects (2)	Constrained Instrumental Variables Fixed Effects (3)
α_{ot}	.975	.791	.600
	(4.48)	(3.16)	(2.54)
α_{ot-1}	.810	.691	...
	(2.60)	(2.39)	
α_{vt}	...	.715	1.04
		(1.60)	(1.70)
α_{vt-1}	...	.450	...
		(.66)	
λ_{ht}	...	...	.780
			(4.38)
Farm equipment: own ($\times 10^{-4}$)	4.26	3.11	2.90
	(2.05)	(2.08)	(2.08)
Farm animals: own ($\times 10^{-4}$)	1.81	.687	.695
	(4.57)	(2.58)	(2.53)
Irrigation assets: own ($\times 10^{-4}$)	.0681	.235	.240
	(.88)	(1.73)	(1.68)
Farm equipment: neighbor ($\times 10^{-4}$)	...	−.0878	−.0194
		(.34)	(.06)
Farm animals: neighbor ($\times 10^{-4}$)	...	−.995	−.948
		(2.08)	(1.85)
Irrigation assets: neighbor ($\times 10^{-4}$)	...	−2.12	−2.07
		(3.58)	(3.38)
Trend ($\times 10^{-2}$)	3.85	4.04	4.07
	(2.54)	(2.65)	(2.53)

NOTE.—HYV use is measured in hectares and asset values in rupees. All variables except education, IADP, and trend are treated as endogenous. Instruments include inherited assets, lagged asset flows, lagged profits, lagged village HYV use, and weighted averages of these variables by village. Absolute asymptotic t-ratios derived from Huber standard errors are in parentheses.

indicating that the effect of an additional hectare of experience was greater in the third period than in the second period.[20]

An additional implication of the equivalence of own and neighbors' experience is that, as indicated in equation (13), the ratio of the coefficients of own to village average experience (α_{ot}/α_{vt}) should be the same as the ratio of the own and village experience (β_{ot}/β_{vt}) coefficients obtained from the profit function. The estimated ratios are remarkably close: The β ratio computed from the linearized profit

[20] While, as noted, the model does not yield strong predictions about the magnitude of λ_{ht}, some insight into the implications of this figure may be gained by noting that if adoption were proportional to experience (λ_{ht} = 1 and no constant term), then HYV acreage would exhibit exponential growth. The fact that this coefficient increases over time suggests that growth will be more than exponential in the initial stages of adoption.

function estimates (table 3, col. 3) is 1.8, and the ratio of the experience (α) coefficients, from column 3 of table 4, is 1.7.[21]

The estimates of the effects of own and neighbors' assets on HYV use also are supportive of the learning-from-others model and suggest that learning externalities are not internalized by the village. In particular, each of the own-asset effects is positive and each of the neighbors' asset effects is negative. With the exception of the own asset effect of irrigation and the neighbors' asset effect of equipment, the estimated coefficients are also significantly different from zero at the 5 percent level or better. When the average coefficients for own assets are used, an increase of 1,000 rupees in the stock of assets owned by a farmer yields a 0.13-hectare increase in HYV adoption. By contrast, an increase of 1,000 rupees in the average stock of assets owned by neighbors results in a 0.10-hectare *decrease* in HYV adoption. While the model does not rule out the possibility that an increase in own and neighbors' assets increases adoption (i.e., there are increasing returns to experience), these estimates are clearly inconsistent with a model in which there is coordinated decision making on the part of the village: under such circumstances, own and village assets should have the same effect on adoption.[22]

V. Simulations Based on Estimated Parameters and Calibration

The HYV decision rule and profit equation estimates can be combined with additional information to describe the dynamics of profit growth and new-technology adoption implicit in the learning model. They can also be used to assess the consequences for technology

[21] As discussed in the Appendix, however, the fact that this ratio is somewhat less than that observed for profits is also consistent with a model with imperfect information in which there are diminishing returns to experience. In either case, the similarity of these results provides good support for the central premise of the model: that own and village experience affect HYVs *only* through their effect on current and future profitability. If, e.g., adoption decisions were driven by rules of thumb or peer group effects, then one might expect a much greater effect of village relative to own experience on adoption than on profitability.

[22] This interpretation of the results assumes that the social planner can reallocate variable assets across land in the same village. In a more restricted model, the planner would allow these assets to be used only on the land owned by the farmer in question. Under these circumstances, own and neighbors' assets may have different effects on the level of HYV acreage by differentially affecting gross cropped area for the different farmers. The effect of an increase in own and neighbors' assets on the *share* of gross cropped area allocated to HYVs should nonetheless be the same for all farmers in the same village. Thus HYV decision rules using the share of area devoted to HYVs as the left-hand-side variable were also estimated. The hypothesis of equal own and neighbor effects was also rejected under this specification (p = .011), with the own and neighbors' asset effects having opposite signs for each asset.

adoption of changes in the distribution of assets. In particular, they permit an assessment of whether the estimated parameters yield an S-curve for adoption and whether the existence of learning from others matters for the temporal patterns and profitability of new-technology adoption.

Although the estimates in tables 3 and 4 provide most of the information necessary to carry out dynamic simulations, some additional information is needed. First, it is necessary to make some assumption about how the level of assets owned by households accumulates over time. This was done by fixing the savings rate, based on detailed savings data available in 1971, at .204, the ratio of net savings to profits among cultivator households. Similarly, gross cropped area (1.9) is based on its 1971 value.

Second, because fixed-effects methods were used to estimate the profit functions and HYV decision rules, no estimates are available for the constants. They were therefore calibrated along with the initial stock of assets by selecting values that matched, given the parameter estimates from tables 3 and 4 and the assumed savings rate and land area, in the third year of the simulation, actual average values of the levels of assets, profits, and HYV use among cultivators in the HYV-using villages in 1971.[23] The constants selected were as follows: the constants in the profit and HYV equations were computed to be 1,428 and $-.166$, respectively, and the initial stock of assets was found to be 1,561 rupees.[24]

One final problem for simulation arises from the implication of the model that the effects of experience are not necessarily constant over time, and we estimate parameters pertaining to only two periods. Diminishing returns to experience in profitability is an implication of the model and was confirmed by the profit function estimates. However, that we directly estimated the structure of the profit function implies that the relationship between experience and profitability can be computed at any point in time. This is clearly not the case for the decision rule in which the complex nature of the problem precludes direct estimation of the structural parameters. The coefficients for

[23] Because the HYVs first became available in the 1968–69 crop year, the figures in 1971 reflect the third year of experience. In addition to providing a systematic way of selecting these constants, calibration using the data is important because the linear approximations of the decision rule may yield inaccurate predictions if they are used to extrapolate well beyond the range of the data used for estimation. Figures for 1971 were used rather than, e.g., for 1968 because information on asset *stocks* was available only in 1971 and because, since this was the final period of the data, the use of the 1971 data minimizes the extent of extrapolation used in computing HYV usage for subsequent years.

[24] This figure reflects only variable assets. Assets that are fixed over time enter, in effect, through the constant in the profit equation.

the adoption equation are thus specific to the second and third years of adoption experience. In order to predict adoption in the fourth or fifth year of the program, therefore, some plausible rule must be used to select the appropriate coefficients.[25]

Fortunately, in contrast to the linear estimates of the profit function, it does not appear that the experience coefficient in the adoption decision equation in the relevant period is changing very much. The estimate of λ_{ht} of .78 reported in table 4 for years 2 and 3 is not significantly different from one at conventional levels (p = .21). Assuming that this relationship continues after the second and third years, one can compute experience coefficients for subsequent years by dividing by this estimated ratio. Thus, for the purposes of the simulation, we assumed that $\alpha_{ot} = \alpha_{o0}/\lambda^t$ and $\alpha_{vt} = \alpha_{v0}/\lambda^t$ for the own and village effects of information, respectively, on HYV use in period t.[26] We also imposed the constraints that HYV acreage should not fall below zero and should not exceed the point at which land is sufficiently unsuited to HYV that, even under perfect information about θ^*, the traditional varieties would be more profitable at the margin than high-yielding varieties.[27]

The importance of learning and learning spillover effects for the profitability of HYVs is illustrated in figure 1, which, for different rates of experimentation, plots the growth in HYV profits per hectare relative to traditional-variety profitability on land that is well suited to new varieties. The dotted line shows profit growth when a constant amount of HYV (0.1 hectare per period) is grown in each period. This shows the diminishing returns to learning in terms of profitability per hectare. In particular, during the initial period when farmers have no experience with the new varieties, profits per hectare are actually negative (−829 rupees). The first 0.1 hectare of experience raises the profitability 1,014 rupees so that HYVs yield positive profits in the second period, although profitability is less than that of traditional varieties (1,136 rupees). The increment to profitability for the second period is only 543 rupees, however. Between the fifth and sixth periods, profits increase by only 168 rupees, although by this point HYVs yield higher profits than traditional varieties do.

[25] Coefficients on experience for the first year are also not available in table 4, but this presents no problem because experience with HYVs is taken to be zero in that period.

[26] An alternate approach is to use the fact that λ_{ht} is not significantly different from one to assert that the effects of experience on adoption remain constant. This change has little effect on the results presented below, and thus we present the simulations only for λ_{ht} = .78.

[27] This latter figure is determined by $A(\eta_h - \sigma_u^2 + \eta_{he} ed)/\eta_{ha}$, where ed is the proportion with primary schooling and A is gross cultivated area.

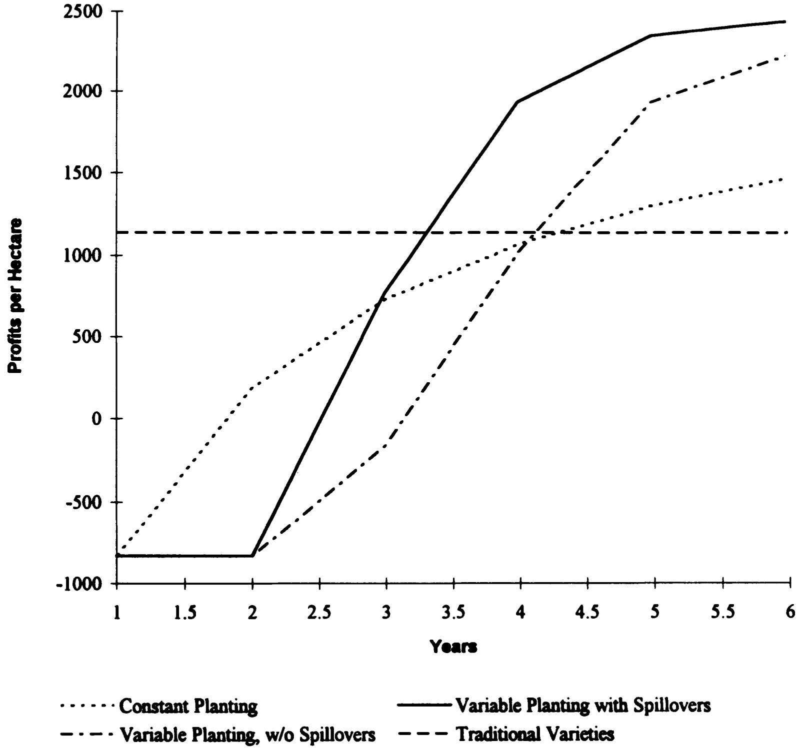

FIG. 1.—Predicted effects of learning on profitability per hectare under various assumptions about adoption and learning.

By contrast, when the rate of planting changes optimally with experience, given the estimated adoption rates of the model, profitability increases dramatically between the third and fourth years. Even if only the profitability effects of own experience are considered,[28] profits increase by 667 rupees between periods 2 and 3 and by 1,185 rupees between periods 3 and 4. Profitability increases even more rapidly when both own and neighbors' experience effects are allowed to affect learning: HYVs become more profitable than traditional varieties almost a year earlier than they do when only own experience affects learning.

To assess the relative importance of own and neighbor learning effects on the temporal patterns of adoption, simulations were performed for farmers and their neighbors differentiated by their initial

[28] These simulations refer to an uneducated farmer with an initial asset stock of 1,561 rupees.

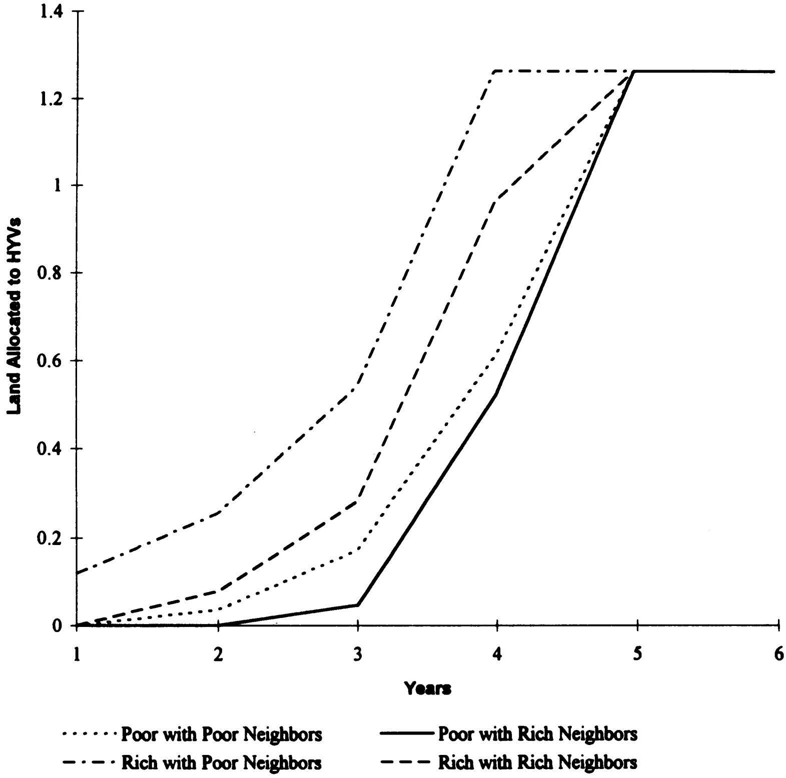

FIG. 2.—Predicted HYV adoption under various assumptions about the initial assets held by a farmer and his neighbors.

asset stocks.[29] The simulation results for adoption are presented in figure 2 for four cases: poor farmers with poor and rich neighbors and rich farmers with poor and rich neighbors. A "poor" farmer (neighbor) is assumed to have an initial asset stock 200 rupees (13 percent) less than the average calibrated value (1,561 rupees), and a "rich" farmer or neighbor is assumed to have an initial asset stock 200 rupees above the calibrated average value. There are a number of striking features of the adoption plots. First, they all follow closely the S-curve that is generally thought to characterize adoption. In this case, the adoption trajectories reflect the accumulation of experience

[29] The simulations are carried out under the assumption that the farmer has no primary schooling, as is the case for the majority of farmers. Simulations assuming that the farmer has primary schooling yield broadly similar results, the main difference being that the initial profits associated with adoption on the most suitable acreage are positive in that case.

and the absence of declines in the effects of experience on adoption. Consider, for example, the adoption curve of a poor farmer with poor neighbors. In the first period, he plants no HYVs, and in the second period, there is a small increase to 0.036 hectare. Over the next two periods, the amount planted to HYVs increases by 0.137 and 0.441 hectares, respectively. By the fifth period, all land suitable to the cultivation of HYVs is planted to these varieties and there is no subsequent increase in adoption.

The simulations also indicate that the rate of adoption is importantly influenced by the production wealth (operation scale) of a farmer and his neighbors. In particular, when the wealth of a farmer's neighbors is held constant, a difference of 400 rupees (29 percent) in a farmer's initial asset stock results in a more than threefold increase in adoption by the third year. Consistent with the finding that wealthier farmers adopt more rapidly and that learning externalities are not internalized in the village, the simulations also indicate that poor farmers with wealthy neighbors are slower to adopt than those with poor neighbors. In particular, the simulations suggest that a farmer whose average neighbor has an initial asset stock of 1,761 rupees does not adopt at all until the third year, although he catches up quite rapidly after that. This catch-up reflects the fact that a farmer who is able to initially rely on his neighbors to undertake experimentation when it is costly (because little experience has been accumulated) will be subsequently wealthier on average than a farmer who has to rely on his own experimentation.

The simulation results indicate that overall gains to profits associated with the adoption of high-yielding varieties, which depend on both profitability per hectare and the amount of the crop that is adopted, are modest, given the evident initial losses that must be sustained in order to benefit from the new technologies. The simulations in figures 1 and 2 indicate that a poor farmer with poor neighbors experiences cumulative profits over an 8-year period following the introduction of the new varieties that are only 7.4 percent higher than those he would have earned staying with traditional varieties. If the poor farmer has wealthier neighbors so that own experimentation can be reduced, however, the relative increase in profits from adopting the new varieties rises to 9.6 percent. The effects are comparable for the better-off farmers.

VI. Conclusions

In this paper we have used a model that incorporates learning by doing and learning spillovers to derive implications for the adoption and profitability of new technologies. Household-level panel data from a nationally representative sample of rural India have then been used to test the main implications of the model as well as to assess the magnitudes of learning spillovers, the extent to which potential learning externalities are internalized, and the implications of these effects for the level and distribution of benefits associated with new technologies.

The primary conclusions of the paper are as follows. First, the estimates indicate that imperfect knowledge about how to use new varieties is a significant barrier to the adoption of these varieties. The fact that own and neighbors' experience influence profitability net of the adoption of HYVs in addition to affecting the rates of adoption suggests that experience effects operate, at least in part, by augmenting the ability of farmers to make appropriate decisions about input use for the new technologies. The rapid decline over time in the effects of experience on profitability indicates, however, that the importance of this barrier substantially diminishes in the first few years of use as experience increases.

Second, we find evidence of learning spillovers. We find that farmers with experienced neighbors are significantly more profitable than those with inexperienced neighbors and, consistent with this result, that the former are likely to devote more of their land to the new technologies. The magnitudes of the effects indicate that a given increase in average experience by a farmer's neighbors increases profitability by almost twice as much as the same increase in own experience. The fact that the effects of own and neighbors' experience on profitability decrease at the same rate between adjacent periods, as predicted by the model, provides further support for the notion that village experience, as with own experience, operates through its effect on knowledge about the correct management of the new varieties.

Third, the estimates indicate that the spillover effects associated with learning from others are small but not unimportant. In terms of adoption, the estimates indicate that a 29 percent increase in own initial assets advances the rate of adoption by about a year and that this results in a somewhat smaller reduction in the rate of adoption on the part of neighbors, who curtail their own costly experimentation. The effect of neighbors' experimentation on the profitability of HYVs is also significant, resulting in a decrease by about a year in the time at which the profitability of HYVs exceeds that of traditional varieties. The overall effects indicate that total profits over an 8-year period following the introduction of HYVs are two percentage points higher when one has neighbors with 29 percent higher initial assets.

The finding that, net of own and neighbors' experience, own and neighbors' assets have opposite effects on adoption indicates that farmers tend to free-ride on the learning of others. Given that optimal learning requires that the marginal profitability of HYVs relative to the traditional crop be negative, a farmer can reduce his losses in a given period if he can rely on his neighbors to gain the relevant experience and then increase his use of the new technology as it becomes more profitable. These results suggest that information on the management of HYVs within the village is not excludable: if information gained by one farmer could be kept from other farmers, then a market for information could arise that compensated farmers for experimentation that benefited other farmers.[30] The results also indicate that there is not sufficient coordination of HYV adoption within the village to generate levels of learning that are socially efficient. Thus these results provide some support for public efforts to increase adoption through subsidies to early adopters.

Appendix A

Effects of Experience on HYV Profits with Village-Level Shocks

Let

$$f(z) = \frac{1}{(1/z) + \sigma_v^2}, \tag{A1}$$

so that the posterior variance presented in equation (8) is

$$\sigma_{\theta jt}^2 = \frac{1}{\rho + \sum_{x=1}^{t} f(\rho_o H_{xt} + \rho_v \overline{H}_{xt})}. \tag{A2}$$

It follows that

$$\frac{\partial \pi_{jt}}{\partial H_{jt-1}} = -\rho_o \sigma_{\theta jt}^4 f'(\rho_o H_{jt-1} + \rho_v \overline{H}_{-jt-1}) H_{jt} \tag{A3}$$

and

$$\frac{\partial \pi_{jt}}{\partial \overline{H}_{-jt-1}} = -\rho_v \sigma_{\theta jt}^4 f'(\rho_o H_{jt-1} + \rho_v \overline{H}_{-jt-1}) H_{jt}. \tag{A4}$$

Note that $f'(z) < 0$ and $f''(z) < 0$. Thus (A3) and (A4) are both positive, and their ratio is ρ_o/ρ_v. Assuming $H_{jt+1} \geq H_{jt} \geq H_{jt-1} > 0$ for all j and thus $\sigma_{\theta jt+1} < \sigma_{\theta jt}$ implies

$$\frac{\partial(\pi_{jt}/H_{jt})}{\partial H_{jt-1}} > \frac{\partial(\pi_{jt+1}/H_{jt+1})}{\partial H_{jt}}.$$

[30] The resulting market would not, in general, yield efficient outcomes because, in the context of our model, information on HYV use is nonrival as well as nonexcludable. See Romer (1990) for a discussion of this distinction.

Thus the own and neighbor experience effects have a constant ratio for all t, and the effects diminish over time as in the case of i.i.d. shocks.

Appendix B

Comparative Statics for the HYV Decision Rule in Period $T - 1$

In order to construct comparative statics for period $T - 1$, we first solve the problem as of period T. At that point, since there are no returns to additional learning and thus there is an interior solution, each farmer sets the differential profitability of HYV to zero, giving

$$H_{jT} = \frac{A}{\eta_{ha}}\left(\eta_h - \sigma_u^2 - \frac{1}{R_{jT}}\right)$$

and

$$V_{jT} = \frac{1}{2}\frac{A_j}{\eta_{ha}}\left(\eta_h - \sigma_u - \frac{1}{R_{jT}}\right)^2 + \eta_a A_j,$$

where the precision of information for j at time t is denoted by $R_{jt} = \rho + \rho_o S_{jt} + \rho_v \bar{S}_{-jT}$. Also, let

$$V_{SS} = \frac{\partial^2 V_T}{\partial^2 S_T} = \frac{\rho_o^2}{R_T^3}\frac{A_j}{\eta_{ha}}\left[-2(\eta_h - \sigma_u^2) + \frac{3}{R_T}\right]$$

and

$$V_{SA} = \frac{\partial V_{jT}}{\partial S_{jT}\partial A_j} = \frac{1}{\eta_{ha}}\left(\eta_h - \sigma_u^2 - \frac{1}{R_T}\right)\frac{1}{R_T^2}.$$

Differentiating the value function at time $T - 1$ for farmer j and each of his n neighbors with respect to their respective HYV use in period $T - 1$ yields $n + 1$ first-order conditions that must jointly hold. Define matrices $\mathbf{M}_H$, where $\mathbf{M}_H[j, j^*] = \partial^2 V_{jT-1}/(\partial H_{jT-1}\partial H_{j^*T-1})$, $\mathbf{M}_S$, where $\mathbf{M}_S[j, j^*] = \partial^2 V_{jT-1}/(\partial H_{jT-1}\partial S_{j^*T-1})$, and $\mathbf{M}_A$, where $\mathbf{M}_A[j, j^*] = \partial^2 V_{jT-1}/(\partial H_{jT-1}\partial A_{j^*})$, for all j and j^* over the range $[1, n + 1]$. Inverting $-\mathbf{M}_H$ and multiplying by $\mathbf{M}_S$ and $\mathbf{M}_A$ yields expressions for the effects of own assets and experience on HYV adoption in period $T - 1$ as well as the effects of the assets and experience of an arbitrary neighbor. Multiplying the latter by the number of neighbors yields expressions for the effects of an increase in average assets and experience on adoption. Thus we have

$$\frac{\partial H_{jT-1}}{\partial S_{jT-1}} = \frac{1}{D}\left(\frac{\rho_o}{R_{T-1}^2} + \delta V_{SS}\right)\left[\frac{\eta_{ha}}{A} - \delta V_{SS}\left(1 + \frac{\rho_v}{\rho_o}\right)\left(1 - \frac{\rho_v}{n\rho_o}\right)\right], \quad \text{(B1)}$$

$$\frac{\partial H_{jT-1}}{\partial \bar{S}_{-jT-1}} = \frac{1}{D}\left(\frac{\rho_o}{R_{T-1}^2} + \delta V_{SS}\right)\frac{\eta_{ha}}{A}\frac{\rho_v}{\rho_o}, \quad \text{(B2)}$$

$$\frac{\partial H_{jT-1}}{\partial A_j} = \frac{1}{D}\left(\eta_{ha}\frac{H_{T-1}}{A^2} + \delta V_{SA}\right)\left[\frac{\eta_{HA}}{A} - \delta V_{SS}\left(1 + \frac{n-1}{n}\frac{\rho_v}{\rho_o}\right)\right], \tag{B3}$$

and

$$\frac{\partial H_{jT-1}}{\partial \bar{A}_{-j}} = \frac{1}{D}\left(\eta_{ha}\frac{H_{T-1}}{A^2} + \delta V_{SA}\right)\frac{\rho_v}{\rho_o}\delta V_{SS}, \tag{B4}$$

where

$$D = \left[\frac{\eta_{ha}}{A} - \delta V_{SS}\left(1 - \frac{\rho_v}{n\rho_o}\right)\right]\left[\frac{\eta_{ha}}{A} - \delta V_{SS}\left(1 + \frac{\rho_v}{\rho_o}\right)\right]. \tag{B5}$$

We assume that interior solutions obtain in each period and restrict attention to equilibria that are stable. Second-order conditions imply that $(\eta_{ha}/A) - \delta V_{SS} > 0$, and thus since neighbors' experience is no more efficient than own experience, $\rho_v/n\rho_o \leq 1$,

$$\frac{\eta_{ha}}{A} - \delta V_{SS}\left(1 - \frac{\rho_v}{\rho_o n}\right) > 0.$$

Local stability of the equilibrium in period $T - 1$ requires $D > 0$, and thus it may be shown that

$$\frac{\eta_{ha}}{A} - \delta V_{SS}\left(1 + \frac{\rho_v}{\rho_o}\right) > 0,$$

$$\frac{\eta_{ha}}{A} - \delta V_{SS}\left(1 - \frac{n-1}{n}\frac{\rho_v}{\rho_o}\right) > 0,$$

and

$$\frac{\eta_{ha}}{A} - \delta V_{SS}\left(1 - \frac{\rho_v}{\rho_o}\right)\left(1 + \frac{\rho_v}{\rho_o}\right) > 0.$$

Also, $V_{SA} > 0$. These conditions are sufficient to establish that own and neighbor effects of experience on adoption as well as the own effect of assets on adoption are positive. The sign of the effect of neighbors' assets on experience is determined by the sign of V_{SS}: if there are increasing returns to experience ($V_{SS} > 0$), then an increase in neighbors' assets will increase adoption; whereas the opposite occurs if there are decreasing returns to experience ($V_{SS} < 0$). As is evident from the expression for V_{SS}, the former effect is likely to be present if experience is low and the latter is likely if experience is high.

The ratio of neighbors' to own experience effects may be written as

$$\frac{\partial H_{jT-1}/\partial \bar{S}_{-jT-1}}{\partial H_{jT-1}/\partial S_{jT-1}} = \frac{\rho_v}{\rho_o}\left[\frac{1}{1 - \frac{A}{\eta_{ha}}\delta V_{SS}\left(1 - \frac{\rho_v}{n\rho_o}\right)\left(1 + \frac{\rho_v}{\rho_o}\right)}\right]. \tag{B6}$$

In the special case in which information from neighbors is equivalent to own information, $\rho_v = n\rho_o$, the estimated ratio of neighbors' to own experience effects is $\rho_v/\rho_o = n$. A similar result obtains if $V_{SS} = 0$. On the other hand, if neighbors' information is imperfect as assumed and $V_{SS} < 0$ ($V_{SS} > 0$), the resulting ratio should be less than (greater than) ρ_v/ρ_o.

References

Bahk, Byong-Hyong, and Gort, Michael. "Decomposing Learning by Doing in New Plants." *J.P.E.* 101 (August 1993): 561–83.

Besley, Timothy, and Case, Anne C. "Modeling Technology Adoption in Developing Countries." *A.E.R. Papers and Proc.* 83 (May 1993): 396–402.

———. "Diffusion as a Learning Process: Evidence from HYV Cotton." Manuscript. Princeton, N.J.: Princeton Univ., Dept. Econ., 1994.

Bliss, C. J., and Stern, N. H. *Palanpur: The Economy of an Indian Village.* New York: Oxford Univ. Press, 1982.

Case, Anne C. "Spatial Patterns in Household Demand." *Econometrica* 59 (July 1991): 953–65.

Evans, William N.; Oates, Wallace E.; and Schwab, Robert. "Measuring Peer Group Effects: A Study of Teenage Behavior." *J.P.E.* 100 (October 1992): 966–91.

Feder, Gershon; Just, Richard E.; and Zilberman, David. "Adoption of Agricultural Innovations in Developing Countries: A Survey." *Econ. Development and Cultural Change* 33 (January 1985): 255–98.

Fudenberg, Drew, and Tirole, Jean. *Game Theory.* Cambridge, Mass.: MIT Press, 1991.

Jovanovic, Boyan, and Nyarko, Yaw. "The Bayesian Foundation of Learning by Doing." Manuscript. New York: New York Univ., Dept. Econ., 1994.

Lucas, Robert E., Jr. "Making a Miracle." *Econometrica* 61 (March 1993): 251–72.

Romer, Paul M. "Increasing Returns and Long-Run Growth." *J.P.E.* 94 (October 1986): 1002–37.

———. "Are Nonconvexities Important for Understanding Growth?" *A.E.R. Papers and Proc.* 80 (May 1990): 97–103.

Schultz, Theodore W. "The Value of the Ability to Deal with Disequilibria." *J. Econ. Literature* 13 (September 1975): 827–46.

Wilson, Robert B. "Informational Economies of Scale." *Bell J. Econ. and Management Sci.* 6 (Spring 1975): 184–95.