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Social learning and parameter uncertainty in irreversible investments: Evidence from greenhouse adoption in northern China

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ABSTRACT

This paper aims at an important gap in the literature, which has not modeled the effect of social learning in a real option context and examined uncertainty-reduction measures through social learning. This paper addresses the gap by modeling social learning as a way of reducing parameter uncertainty, thus facilitating technology adoption and shortening the waiting time in irreversible investments. We use household-level data on intermediate-technology greenhouse adoption in northern China to test the predictions in both a linear probability model and a duration analysis. Our empirical findings support the hypothesis. We also find that market volatility and insecure land property rights discourage adoption.

1. Introduction

Profitability long reigned as the central explanation of adoption and diffusion of new agricultural technologies (Griliches, 1957; Hayami & Ruttan, 1971).[1] Lags and shortfalls in diffusion in the Green Revolution era led agricultural economists to emphasize the role of risk and uncertainty in adoption and diffusion (e.g., Feder, 1980; Roumasset, 1976). They were included in studies of Green Revolution technology adoption to explain lagged or partial adoption or even disadoption. This can be seen as part of a broader literature on the economics of risk and uncertainty and their constraining effects on investment (Newbery & Stiglitz, 1981).

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[1] The dominance of profitability (reflected in relative factor prices and output price) in explaining diffusion of agricultural technology was challenged by Olmstead and Rhode (1993) in the case of the US; they noted that factors such as farmer–seed supplier interactions, crop composition, and regional settlement patterns were important in explaining long term trends in US agricultural technology. They examined, however, evolving technologies and inter-regional differences, so these considerations fall outside of our study's scope as our empirical case is that of adoption of a fixed technology and a single region.

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Information reduces farmers' uncertainty about the payoffs to adopting a new technology. The literature has examined the methods by which farmers receive information in order to evaluate new technologies and operate them well. These methods include receiving information from extension agents, from other farmers ("learning from neighbors"), and from their own experience ("learning by doing") (Besley & Case, 1994; Foster & Rosenzweig, 1995).

The role of "learning from neighbors" has been further refined in recent work on "social learning". Four recent papers exemplify this work. Conley and Udry (2001, 2010) model Ghana farmers' adoption of fertilizer in pineapple production, conditioned by their incomplete information and communication networks with neighbors. Bandiera and Rasul (2006) model Mozambique farmers' adoption of sunflowers conditioned by their social network (neighbors and friends who have adopted). Munshi (2004) models Indian farmers' adoption of HYV seeds of rice and wheat conditioned by neighbors' experiences. These papers demonstrate the effects of social learning on technology adoption. In most cases social learning's effect is interpreted as increasing the capacity of the farmer to adopt as well as reducing the farmer's uncertainty and perception of risk in adoption.

The studies of the impacts of social learning on adoption have, up to now, focused on reversible technologies, such as the examples of those on new crops and new seeds above. But the adoption literature has not yet addressed the issue of how social learning, through its role in reducing risk and uncertainty, conditions adoption of irreversible investments in capital-embodying technology, such as tube wells and greenhouses. Irreversible investments such as building a greenhouse are characterized by the salvage value of the asset being negligible or the asset not being able to be transferred or sold. Because of incomplete information with respect to the performance, reliability, and appropriateness of agricultural equipment, irreversibility entails substantial risk for the investor (Dixit & Pindyck, 1994; Sunding & Zilberman, 2001).

The ability to delay an irreversible investment can be considered as a real option; a higher level of uncertainty regarding future benefits raises the option value and causes the investment decision to deviate from the classical NPV rule.[2] Specifically, investors may rationally delay investment to gain additional information, reduce the level of uncertainty, and increase discounted expected payoffs. While investment delay in the face of uncertainty has been studied in the economics literature (Dixit & Pindyck, 1994; Hassett & Metcalf, 1995; McDonald & Siegel, 1986; Nelson & Amegbeto, 1998; Zilberman, Sunding, Howitt, Dinar, & MacDougall, 1994), this literature has tended to assume that all parameters of the dynamic process are known to agents, and the only uncertainty in the model comes from the future value of the dynamic process.

In contrast, we present a new model wherein, following McDonald and Siegel (1986), we assume that a farmer is considering an investment project, the value of which follows a geometric Brownian motion. Departing from the standard framework, we assume that the true drift of the Brownian motion is unobservable to the farmer (we call this "parameter uncertainty"). In essence, the farmer is imperfectly informed as to the expected rate of return of the farmer's investment. He/she must make an inference about the true expected return based on their information and, at the same time, determine the optimal timing for investing in the project. The farmer can learn about the unknown parameter in two ways: by extracting information on the true drift from a continuous observation of past realized returns on the project value; and by obtaining discrete noisy signals of the true drift. This latter channel represents the process of social learning from early adopters in the farmer's social network.

Furthermore, we empirically model greenhouse investments with primary data collected by the authors in the Shandong province of China. We test both whether social learning induces adoption, and whether social learning shortens the waiting time until adoption, using a duration analysis. The data are multi-year, observing the characteristics, including their social network of prior adopters, of the adopters the year before their adoption. Thus, new to this literature, we capture causality of social learning and adoption.

Previously, investment under parameter uncertainty has been examined in the finance literature. Gennotte (1986) studies portfolio choice under incomplete information about the stock return process. The study uses tools of nonlinear filtering to derive the optimal drift estimator as agents continuously observe the returns. Brennan (1998) and Xia (2001) construct similar models to examine how learning about unknown parameters and unknown predictability affects portfolio choice. Huang and Liu (2007) model learning from discrete noisy signals about the true drift in their study of periodic news on portfolio selection.

The finance literature modeling investment under parameter uncertainty is primarily theoretical, with few empirical applications and none in the domain of investment in agricultural capital as an embodiment of agricultural technology adoption. The present paper addresses this gap in the literature. We analyze irreversible investment under parameter uncertainty, modeling the effect of social learning. The contribution to filling the gap in the literature is both theoretical and empirical.

The rest of the paper is organized as follows. First, we present the theoretical model. Second, we provide background information about greenhouse technology in northern China. Third, we discuss our sample selection and summarize the data. Fourth, we explain our empirical methodology. Fifth, we present the empirical findings from linear probability models and a duration analysis. Finally, we conclude with a summary and policy implications.

[2] The NPV rule could be misleading under irreversible investment because it ignores the fact that the delaying of adoption has its own value, which has to be included as a part of the cost of the investment.

2. The model

We use a real option model to articulate the effect of social learning on technology adoption.[3] We begin with a model of continuous learning, which is essentially that of Abasov (2005). Specifically, a farmer is considering whether to pay a sunk cost of I to start a project with a new technology, whose value V_t evolves according to:

$$dV_t = V_t(\mu dt + \sigma dZ_t), \tag{2.1}$$

where Z_t is a standard Brownian motion and μ and σ are its drift and volatility, respectively.

Motivated by Merton (1980), the farmer can observe V_t continuously and estimates its volatility σ; however, he/she only knows that the drift μ is a normal random variable with mean m_0 and variance γ_0 in the beginning.[4] According to Lipster and Shiryaev (1978), the conditional mean of the drift given the farmer's information set F_t^V (which contains the history of the project value up to time t), $m_t = E(\mu|\mathrm{F}_t^V)$, follows:

$$dm_t = \frac{\gamma_t}{\sigma} dZ'_t, \tag{2.2}$$

where $\gamma_t = E[(\mu - m_t)^2|\mathrm{F}_t^V]$ is the conditional variance of the drift, satisfying:

$$d\gamma_t = -\frac{\gamma_t^2}{\sigma^2} dt, \tag{2.3}$$

and Z'_t is a Brownian motion with respect to the farmer's information set F_t^V. The process Z'_t is related to the original Brownian motion through:

$$\mathrm{d}Z'_t = \mathrm{d}Z_t + \frac{\mu - m_t}{\sigma} \mathrm{d}t. \tag{2.4}$$

We can solve Eq. (2.3) for γ_t:

$$\gamma_t = \frac{\gamma_0 \sigma^2}{\gamma_0 t + \sigma^2}. \tag{2.5}$$

This result shows that continuous learning decreases the conditional variance of the unknown parameter. Thus the longer the farmer observes the value process, the less uncertain he/she is about the drift. This is consistent with the results of Merton (1980): the uncertainty of the drift is not related to the number of observations, but rather to the length of the observation period. However, the conditional mean of the drift can fluctuate up or down, depending on new observations of the Brownian motion Z'_t.[5]

According to Gennotte (1986), the farmer's decision can be separated into two problems: 1) the inference of the unknown parameters given the farmer's information set F_t^V and 2) the farmer is seeking to maximize his/her expected utility by choosing the time (the optimal stopping time) to make the investment. Putting everything together, we can characterize the farmer's problem using observable processes:

$$\begin{aligned} J(m_0, \gamma_0, V_0) = \max_{\tau \in \mathrm{F}^V} & E\left[e^{-\rho\tau}(V_\tau - I)\right], \\ s.t.\ \ dV_t &= V_t\left(m_t dt + \sigma dZ'_t\right), \\ dm_t &= \frac{\gamma_t}{\sigma} dZ'_t, \\ d\gamma_t &= -\frac{\gamma_t^2}{\sigma^2} dt. \end{aligned} \tag{2.6}$$

Here, J is the farmer's value function assuming that the optimal investment policy is followed, σ is the discount rate, and τ is an F_t^V-stopping time, reflecting the fact that the farmer must make a decision based on the available information. The stopping rule takes the form of:

$$\tau = \inf\left\{t \geq 0 : V_t \geq V^*(m_t, \gamma_t)\right\}, \tag{2.7}$$

where $V^*(m_t,\gamma_t)$ is the trigger value of investing, which depends on the state variables.[6]

[3] The value of the Brownian motion model is to provide an explicit mechanism to show how social learning facilitates greenhouse adoption when farmers face an irreversible investment under uncertainty.

[4] Merton (1980) shows that the variance of the return can be estimated precisely from continuous observations on a finite interval, but not the mean return unless the length of the interval becomes large.

[5] By observing the project value V_t, the farmer can compute the conditional drift m_t and infer Z'_t. Since he/she does not observe the true drift μ, the original Brownian motion Z_t is not observed. In a world where μ is known, Z'_t simply becomes an Ito process with respect to the Brownian motion Z_t and $\mathrm{d}Z'_t$ and $\mathrm{d}Z_t$ are perfectly correlated.

[6] Since γ_t is a deterministic function of t, we can equivalently formulate the problem in terms of state variables (m_t,t).

To understand the intuition of the solutions to the farmer's optimization problem, recall that in the standard real option problem of McDonald and Siegel (1986) and Dixit and Pindyck (1994) without parameter uncertainty, the trigger value of investing increases with the drift μ and volatility σ of the project value. The intuition is that greater drift and volatility encourage the investor to wait because they make it more likely that the investor will receive a higher project value in the future.

Abasov (2005) derives the Hamilton–Jacobi–Bellman equation for the optimal stopping problem (2.6) and transforms it into a linear complementarity problem, which he solves with the finite difference method. His numerical results demonstrate that the trigger value of investing, $V^*(m,\gamma)$, obtained as a part of the solution, increases with m and γ. This result is consistent with the conditional drift m replacing the observed drift μ in the standard real option problem, and the fact that parameter uncertainty (through the conditional variance of the drift) further contributes to the overall uncertainty surrounding the project value.

In developed countries, there are public economic forecasts and newsletters informing investors. Therefore, agents can make inferences based on past realized returns. However, in rural China, information is more likely to come from local private sources. Similar to Huang and Liu (2007), we allow farmers to obtain direct signals of the drift from early adopters in their social networks. These signals are noisy, reflecting the fact that even early adopters are unlikely to learn everything about the technology from their own experience. Different from Huang and Liu (2007), we assume that the signals are costless. However, the number of signals to which a farmer has access is limited by the scope of his/her social network, which we take as exogenous. For simplicity, we also assume that these signals are received at time 0, just as the farmer begins to consider the adoption decision. Since discrete signals are more effective than continuous learning in changing the farmer's belief, it seems reasonable to assume that he/she would seek out these signals at the beginning of their decision-making process.[7] This implies that discrete updating affects the farmer's optimal stopping problem only insofar as it changes his/her initial belief; discrete updating plays no role in the dynamics of the conditional mean and conditional volatility.

Let the ith signal be given by:

$$\mu_i = \mu + \varepsilon_i, \tag{2.8}$$

where $\varepsilon_i \sim N(0,\sigma_\varepsilon^2)$ is independently and identically distributed. After receiving n such signals at time 0, it can be shown that the conditional mean and variance of the drift are given by:

$$m'_0 = \frac{\sigma_\varepsilon^2}{n\gamma_0 + \sigma_\varepsilon^2} m_0 + \frac{n\gamma_0}{n\gamma_0 + \sigma_\varepsilon^2}\overline{\mu}, \tag{2.9}$$

$$\gamma'_0 = \frac{\gamma_0\sigma_\varepsilon^2}{n\gamma_0 + \sigma_\varepsilon^2}, \tag{2.10}$$

where $\overline{\mu} = \frac{1}{n}\sum_{i=1}^{n}\mu_i$. Eq. (2.10) shows that the conditional variance is decreasing in the number of signals, which can be taken as the scope of social learning. Therefore, social learning reduces parameter uncertainty. Using Abasov's numerical results, this implies that social learning decreases the threshold value for adoption, making it easier for the threshold value to be breached, leading to shorter waiting time for technology adoption.

Considering the conditional mean Eq. (2.9), we find that as the number of signals increases, m'_0 tends to move away from m_0 and approach $\overline{u}$. This indicates that social learning causes the farmer's belief about the drift to converge to the average belief in the farmer's social network. The net effect depends on the relation between m_0 and $\overline{u}$. If $m_0 > \overline{u}$, the farmer is initially too optimistic; social learning causes him/her to lower their expectation about the project's return. This, in turn, lowers the trigger value and facilitates adoption. If the farmer is unbiased in his/her initial belief, then social learning is unlikely to change the probability of adoption through its effect on the conditional mean return.

If we generalize this model to allow the dynamics of social learning to enter the farmer's decision making, then we can write down the following optimal stopping problem, where we combine continuous filtering with discrete updating:

$$\begin{aligned} J(m_0,\gamma_0,V_0) &= \max_{\tau \in F^V \vee F^N} E\left[e^{-\rho\tau}(V_\tau - I)\right], \\ s.t.\ dV_t &= V_t\left(m_t dt + \sigma dZ'_t\right), \\ dm_t &= \frac{\gamma_t}{\sigma} dZ'_t + \frac{\gamma_{t-}}{\gamma_{t-} + \sigma_\varepsilon^2}(\mu_t - m_{t-})dN_t, \\ d\gamma_t &= -\frac{\gamma_t^2}{\sigma^2}dt - \frac{\gamma_{t-}^2}{\gamma_{t-} + \sigma_\varepsilon^2}dNt. \end{aligned} \tag{2.11}$$

Here, μ_t refers to the independently and identically distributed noisy signals described in Eq. (2.8), and N_t is a counting process that counts the number of signals that the farmer has received up to time t.[8] It can be periodic and deterministic as in Huang and Liu (2007), or stochastic, as in the case of a Poisson process with arrival rate λ, which describes the timing of social interactions as

7 By definition, discrete updating (2.9) causes the conditional mean to change by a finite amount, while continuous updating (2.2) yields only infinitesimal changes over an instant.

8 Because the sample path of the jump process N_t is right continuous, we use the notation m_{t-} and γ_{t-} to denote the left limit of the conditional mean and variance, respectively. Essentially, they denote the values of these processes just before the arrival of a discrete updating.

a random phenomenon. In all cases, however, the first part of the dynamic equations for (m_t,γ_t) captures the effect of continuous updating as the farmer learns from the past history of V_t. The second part represents a jump in the conditional mean and variance when the farmer receives a noisy signal of the drift. Because γ_t and N_t are deterministically related through the conditional variance relation, we have suppressed the dependence of the value function on N_0. Similarly, we can write the trigger value as $V^*(m_t,\gamma_t)$, with the understanding that the effect of N_t is already reflected in the conditional variance γ_t.

Generally, the optimal stopping problem (2.11) must be solved numerically. To the extent that social learning affects the conditional mean and variance of the drift, it also affects the farmer's adoption decision. According to the above model, the amount of social learning is measured by N_t. As the conditional variance equation shows, a larger N_t (more social learning) always reduces γ_t, while the effect through the conditional mean equation is ambiguous (probably negligible when m_0 is close to the average signal). If the trigger value $V^*(m_t,\gamma_t)$ in problem (2.11) is increasing in γ_t (which seems to be an intuitive conjecture without actually solving the problem using numerical techniques), this would imply that social learning can lower the trigger level for adoption.

Summarizing the various models, the classical real option analysis of McDonald and Siegel (1986) predicts that the trigger value for investment increases with the uncertainty of the project value. We show that this result also extends to parameter uncertainty. We argue that social learning can facilitate adoption by reducing the trigger value through lower parameter uncertainty, and a lower trigger value makes adoption easier for farmers (resulting in less waiting time). In rural China, where public extension information is not easily accessible to small farmers, information from social learning could play an important role in their adoption decisions. The rest of our paper is dedicated to testing this hypothesis.

3. Greenhouse intermediate-technology in northern China

Before economic reforms, China gave first priority to the development of heavy industry. In agriculture, China emphasized the importance of self-sufficiency for grains — the “iron rice bowl policy.” After the “household responsibility system” reform started in 1981, the shortage of grain supply was relieved by a significant increase in grain production. This made it possible for China to diversify into horticulture and livestock husbandry. Meanwhile, rapid income growth in the 1980s and 1990s created an increasing demand for vegetables and fruits.

The huge demand for fresh vegetables led to the development and widespread diffusion of an affordable greenhouse technology for northern Chinese farmers. Rather than the modern, expensive type made of steel frame, plastic or glass walls and ceilings, and requiring energy-using heating and cooling mechanisms (promoted in the 1970s in China but had very little adoption because of the cost (Wan, 2000)), the greenhouse adopted in the 1990s in northern China is of the “intermediate technology” type, which was first created by Shandong farmers in the early 1980s. This type of greenhouse is made of simple clay walls, a bamboo frame, a plastic-sheet roof, and a straw mat roll-out awning for cold nights. The sun warms the interior; the greenhouse is built with an orientation to maximize sunlight capture. These greenhouses changed not only the food consumption pattern for hundreds of millions of consumers, but also the face of farming in northern China. They helped to transform China from a modest global player to the volume leader in horticulture — China grew 47% of the vegetable volume in the world by 2004 (Weinberger & Lumpkin, 2005). The vegetable greenhouse area in China reached 723,000 ha at the end of 2006 (NBS, 2008), and the output of greenhouse vegetables reached about $60 billion and provided about 40 million jobs in rural China in 2008 (Ma, 2009).

The intermediate-technology greenhouse is far cheaper than a modern type, but is still a major investment for the small farmers in Shandong. The construction cost of intermediate-technology greenhouses is roughly four dollars per square meter, much cheaper than modern greenhouses made of glass or plastic, which cost about 70 dollars per square meter to construct. Yet, even four dollars per square meter is a large investment for small farmers. For example, if a greenhouse is 60 m long and 10 m wide, the construction cost would be about $2400, while the average Chinese farmer earned less than $500 in 2005. Moreover, the labor involved in building the greenhouse is substantial; the farmer often spends months creating the main component — the rear-wall of the greenhouse, which is usually made of pounded clay bricks.

In addition, the investment is “irreversible,” in the sense of Bertola and Caballero (1994), as the structure can only be used in immediate production, and has little to no salvage value and cannot be sold or transferred (the structure is not movable). If the farmer decides to demolish the greenhouse, the bricks would most likely be broken into dirt clods, and the old straw awning and old bamboo beams are worth little in salvage.

Greenhouse vegetable growing is different from open-field vegetable growing in several ways. First, greenhouse yields far exceed open-field yields. For example, the tomato yield is about 12 tons per mu (as there are 15 mu in 1 ha, that is about 180 tons per ha) annually in a greenhouse, compared to about 2 tons per mu (30 tons/ha) in an open field. Several factors, including a longer growing season, multiple harvests, and labor-intensive production, contribute to the higher yield. Second, the greenhouse growing season lasts for about 9 months during the fall and the spring, while open-field growing lasts for about 3 months during the summer in northern China. Third, greenhouse-grown vegetables are often transported to distant markets, while vegetables from the open-field are usually used for home-consumption, with a small surplus sold in local markets. These considerations suggest that there is little overlap or competition between greenhouse and open-field growing.

4. Sample selection and survey methods

Our survey area is in Shandong province, the leading horticulture province in China. It has seven percent of China's cropland, but 12% of China's horticultural land in 2004. The latter share has been rising over time. The number of greenhouses and the level of commercialization as well as yields in Shandong are higher than in the rest of China.

In Shandong, we conducted two coordinated community and household level surveys in 2005 and 2006, respectively. The first one, the Shandong village survey, provided a representative sample of tomato and cucumber growing villages in Shandong.[9] During the first step of the survey, we created sampling frames of county-level tomato and cucumber production in order to select five sample counties per crop. Specifically, with knowledge of county production of each crop, we ranked counties by the output per capita of that crop. For each crop in our sample, one high production county was randomly selected from the counties in the top quintile; the other high production county was randomly selected from the second quintile. The two medium production counties were randomly chosen from the third and fourth quintiles, respectively. After eliminating five percent of the counties with the lowest production, the low production county was randomly chosen from the lowest quintile. In the end, there were two counties in the high production set, two counties in the medium production set, and one county in the low production set.

After the sample counties were chosen, a similar process was used to select sample townships from the counties and sample villages from the townships. For each crop, the survey teams visited a total of 10 townships. Moreover, for each crop (among the ten townships), we interviewed respondents in 35 villages (22 in high production counties, 10 in medium production counties, and 3 in low production counties). Since we collected area data on all villages, townships, and counties in the sample, we were able to construct area-based weights in order to create point estimates of our variables that are provincially representative.

Having selected the villages, the enumeration team visited each community and undertook data collection. Specifically, the enumerator conducted a two-hour interview with three village leaders for the village survey. To select households from the selected villages, we followed the following steps. Here we use cucumber villages as example. We divided all households in each village into two groups: cucumber households and non-cucumber households. Then we applied the following rules to select households: 1) in villages with more than (or equal to) 7 cucumber households, we randomly sampled (or selected all) 7 cucumber households and 3 non-cucumber households; 2) in villages with 5 or 6 six cucumber households, we selected all these cucumber households and randomly sampled 3 non-cucumber farmers; and 3) in villages with less than 5 cucumber households, we also selected all these cucumber farmers and then randomly sampled 2 non-cucumber farmers. As a result, we obtained 655 observations in our sample, and 326 households from cucumber villages, of which, 227 households grew cucumber and 99 households did not grow cucumber in 2006. Following the same approaches, we also obtained 329 households from tomato growing villages, of which 229 households grew tomatoes and 100 household did not grow tomatoes. The total number of households that grew either cucumbers or tomatoes in 2006 was 456 (199 households grew neither cucumbers nor tomatoes in 2006). With knowledge of the distribution of cucumber (or tomato) households and non-cucumber (non-tomato) households, plus the distribution of greenhouse adopters in each village, we calculated weights for our selected sample in order to better represent the population distribution.

Shandong farmers did not adopt greenhouses all at once, but rather, in a process typical of diffusion of new technology, over the years. Some households adopted greenhouses as early as the 1980s (the earliest adoption was in 1984 in the survey), but the recall errors in those early adoptions could deteriorate the quality of data even though farmers claim that they can remember the details of their own adoption because adoption represented substantial investment to them. In order to minimize recall error, we only retained in our sample data on adopters whose adoption was not earlier than 1996, and all information for non-adopters was taken from 2001 (the middle point of 1996 and 2006, following Carletto, Kirk, & Winters, 2010) to minimize heterogeneity over time.

After data cleaning, we obtained 485 valid observations for regressions (242 growers from tomato villages and 243 growers from cucumber villages).[10] Among this sample, 221 households (46%) were found to have adopted greenhouses, while 264 households were found to have not adopted greenhouses. 137 adopters out of the 221 households are tomato growers, and a higher share of tomato growers adopted greenhouses apparently due to the fact that in cucumber production a shading shed is a substitute for a greenhouse, while in tomato production there is no substitute for a greenhouse, and the only options are growing in the open field or in a greenhouse.

4.1. Measures of and patterns in social learning among sample households

We are interested in the effect of social learning on farmers' adoption of greenhouses. Our theoretical model predicts that social learning helps to reduce uncertainty, thus facilitating adoption and shortening waiting time. Empirically, however, social learning could be one of many factors affecting adoption. For example, farmers may have other options such as off-farm employment. Alternatively, farmers may be liquidity-constrained because greenhouse adoption is a major investment. To disentangle the effect of social learning from other determinants, we need to find appropriate empirical proxies for social learning and control for other factors that might influence farmers' decisions.

Social learning is a key variable in our study. We measure social learning in a way similar to that of Bandiera and Rasul (2006). We asked farmers in the following way: “Of all people you know, how many households are there? And how many of those households adopted greenhouses before you?” We then asked, “How many of these people are your relatives and friends,

[9] We did not directly stratify on greenhouse use because our survey was part of a large horticulture survey, which required stratified sampling of cucumber/tomato and non-cucumber/tomato households. Cucumber and tomato are the two most popular greenhouse crops in the sampling area, and we are able to adjust for selection bias with knowledge of the distribution of crops and greenhouse use in each village.

[10] Two reasons required our reducing the number of observations from 655 to 485 in the regressions: first, we needed to remove inconsistent records from the original dataset (removing 34 observations). Second, as we discussed above, we only kept data on adoption that was not earlier than 1996 to minimize the recall error (removing 136 observations). We have adjusted the data used in the regressions for the above attrition with knowledge of each removed observation and its corresponding weight in the sample.

respectively?" (We did not include neighbors as a separate category because Chinese farmers usually consider neighbors among friends). We asked the non-adopters how many adopters were in their village in 2001 and 2006 (the time of the survey). The answer to the second question is taken as our empirical proxy for social learning. Differing from Bandiera and Rasul (2006) (who asked about the social network at the time of the survey, not before adoption), we obtained the size of the farmer's social network of adopters *before* the farmer's adoption, so that we can infer causality.

There are several reasons why our measure of the social network of adopters is an appropriate measure of social learning before adoption. First, the number of earlier adopters among relatives and friends is likely to be positively correlated with the number of different sources of information on greenhouse adoption that the farmer accessed before adoption, which corresponds to the number of discrete signals in our theoretical model. Second, village membership, kinship, and friends are the defining elements of a farmer's social network, or a group of people with whom the farmer has close contact, and from whom information can be most easily obtained. By concentrating on the number of earlier adopters among relatives and friends, we also mitigate the concern for ex post social network formation. While this is obvious for kin adopters, we noticed during our survey that Shandong farmers tended to define friendship based on long-term relationships, such as classmates, neighbors, and people who served with them in the army. Typically, they consider a friend someone from whom they can borrow money in case of illness; they would not consider passing acquaintances as friends. Third, farmers told us they were easily able to remember the number of adopters they knew before they adopted; we surmise that this is because a greenhouse is a big investment for local farmers and hence easily recalled.

The first two rows of Table 1 provide the means and standard errors of our social learning measures by adoption status. In the last column, tests of equality of the means are provided to examine whether the differences between adopters and non-adopters are significant. The first row indicates that, on average, adopters know about 8.1 earlier adopters among relatives and friends in their own village, while non-adopters only know about 4.8 earlier adopters in their social network. The result of the *t*-test shows that this difference is significant. This implies that there is more social learning for adopters than for non-adopters. When we extend the scope of the social network to include earlier adopters among relatives and friends in nearby villages (the second row), the findings are similar.

4.2. Other sample household characteristics

Table 1 presents other household characteristics by adoption status. There are several salient features.

(1) Non-adopters have more years of awareness of greenhouse technology than adopters, which suggests that non-adoption is not likely caused by later awareness or unawareness of the technology.
(2) The family size of adopters is larger than that of non-adopters, while the amount of farm laborers in the family is significantly smaller for adopters than for non-adopters. This is because adopters have more dependent family members (either young children or old parents) than non-adopters. For such households, greenhouse adoption may be chosen because it allows the adults to work close to home, so that they can care for dependent family members. Non-adopters are, on average, substantially older than adopters — a point consistent with younger farmers having more young children and old parents to care for.
(3) Off-farm income is significantly larger for non-adopters than for adopters, which suggests that greenhouse labor and off-farm employment are substitutes.

Table 1
Descriptive statistics: household level data.
The sample period in this study ranges from 1996 through 2006, and this table contains the basic household characteristics used in our study. The mean value for each variable is presented with the associated standard error in parentheses. For adopters, all variables are measured in the year before adoption. For non-adopters, all variables are measured in 2001 (the middle point between 1996 and 2006). *** denotes significance at one-percent, ** five-percent, and * ten-percent levels. Data used in this table is from the field survey described in Section 4.

Basic characteristics	Non-adopter	Adopter	Test of equality of the means (*p*-value)
Social learning within village	4.760 (0.709)	8.079 (0.956)	0.004***
Social learning within village and nearby villages	5.815 (0.797)	9.898 (1.096)	0.002**
Years of awareness of the technology	7.894 (0.435)	5.287 (0.308)	0.00***
Family size (person)	3.763 (0.071)	3.942 (0.075)	0.086*
Family labor (person)	2.931 (0.069)	2.562 (0.056)	0.001***
Age of family head (year)	42.58 (0.611)	37.06 (0.582)	0.00***
Total schooling years	12.83 (4.794)	12.54 (5.334)	0.528
Off-farm income (10,000 yuan)	1.215 (0.143)	0.657 (0.080)	0.01***
Farm size (mu)	5.321 (0.171)	6.710 (0.228)	0.01***
Irrigation ratio	0.804 (0.019)	0.912 (0.015)	0.01***
Ratio of construction costs	3.239 (0.222)	1.766 (0.137)	0.00***
Number of major land reallocations	1.381 (0.069)	0.964 (0.068)	0.00***
Distance to neighborhood (minutes)	15.36 (0.641)	16.62 (0.913)	0.246
Surname ranking	1.858 (0.072)	1.862 (0.081)	0.969

(4) There is no significant difference in education (total schooling years) between adopter and non-adopter households in our sample. This suggests that education might not be the main determinant of greenhouse adoption and that other sources of information, such as social learning, play a role.
(5) The farm size of adopters is larger than that of non-adopters, which may be because adoption requires wealth correlated with land, or that farmers with more land tend to focus on farming for income (rather than off-farm work), and thence to favor investments to raise productivity of farming.
(6) Irrigation is (for physical reasons) important to greenhouse farming, and 91% of the adopters have irrigation. By contrast, 80% of the non-adopters have irrigation.
(7) Adopters have greater land tenure security (have experienced fewer land reallocations) than non-adopters. This appears to correlate with the long-term nature of greenhouse investment.
(8) The presence of a credit constraint would in theory undermine an important investment such as greenhouses, all else equal. However, it is difficult to measure the credit constraint of a farmer, as this is equivalent to examining whether the farmer can borrow as much as he/she would like at the going market interest rate (Banerjee & Duflo, 2002). Since we are focusing on greenhouse adoption rather than testing whether the farmer has invested in a greenhouse of optimal scale, we only need to know whether the farmer is capable of building a greenhouse by borrowing money or using savings. Therefore, we identify the housing construction cost prior to greenhouse adoption as a proxy for the financial capacity of a household. We also collect the greenhouse construction cost for each household, and use the ratio of the two construction costs as an indicator of potential credit constraints.[11] The data for this ratio indicate that the housing construction cost is greater than the greenhouse construction cost for both adopters and non-adopters. More importantly, the ratio for non-adopters is 3.2, which is significantly greater than the ratio for adopters, which is 1.8. This suggests that non-adopters are less likely to face credit constraints than adopters.
(9) Although adopters tend to experience more social learning, this is not because they have larger social networks. Since it is not easy to ask farmers to identify their total number of friends, we use the surname quartile ranking in the village as a proxy of the farmer's social network since lineage is still very important in rural China.[12] This variable takes the value of 1 to 4, with 1 indicating that the farmer's surname is among the largest surname lineages in the village. The data indicates that, on average, non-adopters have no difference in surname ranking than adopters, which implies that adopters do not have larger general social networks than non-adopters.
(10) Adopters live further away from the road compared to non-adopters, which suggests that people adopt greenhouse technology not because of lower product delivery costs from living closer to the road. Instead, living closer to the road might be correlated with more off-farm job opportunities, which could discourage greenhouse adoption.
(11) We also collect information about greenhouse subsidies from the government by asking farmers the following question: "How much subsidy did you receive from the village or town government when you built your greenhouse?" The results from the survey show that only 30 out 501 households received a subsidy and the amount ranged from 80 yuan to 1000 yuan (about 10 to 125 US dollars), which is a small fraction of a greenhouse's construction cost; this suggests that greenhouse subsidy played little role in adoption.[13]

5. Empirical approach

In this section, we present the empirical approach and show its connection to our theoretical model.

5.1. Linear probability model

According to our real option model of greenhouse adoption, the farmer decides to adopt or to wait based on a comparison between the current value of the technology and the trigger value. Therefore, we can define the farmer's adoption status (Y_t) at time t as:

$$\begin{aligned} Y_t &= 1(\text{adopt}), \ \text{if } Y_t^* = V_t - V_t^* > 0, \\ Y_t &= 0(\text{non-adopt}), \text{if } Y_t^* = V_t - V_t^* \leq 0, \end{aligned} \tag{5.1}$$

where V_t is the discounted expected value of all future cash flow from greenhouse vegetable production, and V_t^* is the trigger value.

McDonald and Siegel's (1986) model, in which the drift μ is known, shows the trigger value V^* as a function of the parameters (ρ,μ,I,σ). However, the drift μ is unknown in our model. Thus, the trigger value also depends on the conditional mean and variance

[11] For non-adopters, we use the average construction cost of greenhouse in the village as the proxy for the construction cost.
[12] In rural China, the same surname is important to the social network in the village; for example, the leader of the village is often from the largest surname lineage in the village (Shen & Yao, 2006).
[13] Since a greenhouse subsidy is available only if the farmer builds the greenhouse, non-adopters are not able to obtain the subsidy and we do not include this variable in Table 1.

of the drift, (m_t, γ_t). According to the dynamics of (m_t, γ_t) in Eq. (2.11), we can substitute (m_t, γ_t) with functions of $\left(m_0, \gamma_0, Z'_t, N_t, \sigma, \sigma_\varepsilon, \overline{\mu}\right)$.[14] Therefore, we can express the trigger value V_t^* as:

$$V_t^* = g\left(\rho, I, \sigma, m_0, \gamma_0, Z'_t, N_t, \sigma_\varepsilon, \overline{\mu}\right). \tag{5.2}$$

Following similar reasoning, the current project value V_t can be written as a function of the same group of variables. Therefore, we can express $Y_t^* = V_t - V_t^*$ as:

$$Y_t^* = h\left(\rho, I, \sigma, m_0, \gamma_0, Z'_t, N_t, \sigma_\varepsilon, \overline{\mu}\right). \tag{5.3}$$

To motivate the empirical proxies for the variables in Eq. (5.3), we first note that Z'_t represents the stochastic change in the project value. A good proxy for Z'_t is the observed profitability of greenhouse production in the current period. We measure profitability by the ratio of the output price to the input price.[15] Because historical data are not available on vegetable prices in Shandong, we use the ratio of the vegetable price index and the input price index at the national level as a proxy for the profitability of greenhouse production over the years.[16] The investment cost I is embedded in the ratio of the housing construction cost and greenhouse construction cost.

Continuing with the interpretation of Eq. (5.3), σ is the volatility of the project value, which we measure as the standard deviation of the national vegetable price index over the three years prior to the farmer's adoption. $\overline{\mu}$ represents the average signal received by the farmer from the farmer's social network, the proxy for which is the vegetable price index growth rate over the three years preceding the farmer's adoption. This is a reasonable assumption if the expected return of the project is close to the average return in the economy. As noted above, N_t is the key variable in our study. We measure it by the number of earlier adopters in a farmer's social network, which includes relatives and friends in the farmer's own village and nearby villages.

Besides these theoretically motivated variables, there may be other factors that affect greenhouse adoption in practice, such as land tenure security, off-farm income, and household characteristics. These factors were discussed in the preceding section. In addition, we do not have compelling empirical proxies for the farmer's discount factor ρ, their initial values of the conditional mean and variance (m_0, γ_0) before any learning had taken place, and the standard deviation of their signals σ_ε. These parameters, however, are likely correlated with household characteristics such as age, family size, and education, which we include in our empirical analysis to capture potentially omitted factors.

Our theoretical model is based on observables; with knowledge of these observables, the model predicts adoption with certainty. In reality, however, we do not observe all information relevant for determining adoption. Therefore, our empirical model must allow for the presence of unobserved determinants.

In brief, our empirical model can be written as:

$$Y_i^* = f(X_i, Z_i, N_i, D) + e_i, \tag{5.4}$$

where i denotes a household, Y_i^* is the adoption criterion in year t according to Eq. (5.1), and X_i are household characteristics before adoption (in year $t-1$), which include the age, total schooling years of the household, family size, farm size, off-farm income, irrigation conditions, ratio of housing to greenhouse construction costs, greenhouse subsidy, input price (urea), distance to road and surname ranking (by number of persons in the village with the given surname as a proxy for the overall social network). Z_i is the institutional and market variables at $t-1$, which include the number of major land reallocations experienced by the household, the ratio of the output price index to the input price index, the volatility of the vegetable price index, and the average growth rate of the vegetable price index. N_i is the number of earlier adopters in the farmer's social network at $t-1$. D represents village and crop dummies that control for heterogeneity in farmers' adoption decisions across different villages and crops. Finally, e_i represents the effect of unobservable determinants of adoption. The probability of adoption is:

$$P\left(Y_i^* > 0\right) = P(e_i > -f(X_i, Z_i, N_i, D)). \tag{5.5}$$

In our empirical analysis, we estimate a linear probability model (LPM), which specifies the above probability as a linear function of the explanatory variables. The LPM enables us to use village dummies to control for heterogeneities across villages, which is important given the structure of our dataset (which pools households from different villages).[17]

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[14] This is only a simplified representation; strictly speaking, the solution of (m_t, γ_t) according to Eq. (2.11) depends on the paths of Z'_t and N_t, as well as the history of the signals up to time t.

[15] In this paper we focus on the greenhouse adoption decision, which is essentially the comparison between adopters and non-adopters within a village in most cases. For non-adopters, the natural benchmarks for them are the average yield and input level from adopters in the same village. In this sense, what really matter for an adoption decision are the output and input prices over time, which can be well captured by the ratio of output price to input price. In addition, we have included village dummies and crop dummies in the empirical models to control for heterogeneities in the yield and input level across villages and crops.

[16] The national price index is likely in line with the Shandong price index since Shandong province has been a major greenhouse vegetable production area in China and the Shouguang wholesale market (Shandong) is the largest greenhouse vegetable wholesale market in China.

[17] The LPM model is more robust than Probit and Logit models at the cost of yielding less efficient estimates. Since our first priority is to maintain robustness, we focus on results from the LPM model. For robustness check, we also provide the results estimated from Probit and Logit models (see Table 6). These results are similar to those from the LPM model.

5.2. Duration analysis

From the theoretical framework presented above, we can see that social learning facilitates adoption through reducing the trigger value. On one hand, we can test whether social learning facilitates final adoption through the linear probability model. On the other hand, a lower trigger value also corresponds to a shorter waiting time, and the waiting time is defined as the number of years between the year when a farmer first observes someone adopting the greenhouse technology in his/her village and the year of his/her own greenhouse adoption. In order to test the relation between social learning and waiting time, we employ a duration analysis to model the dynamic nature of the adoption process with time-varying covariates.

Unlike most duration analyses which focus on hazard functions (for example, Carletto et al. (2010)), in this paper we are primarily interested in the effect of the covariates on the expected duration. Consequently, we can apply a censored Tobit analysis to the log of the duration (page 698, Wooldridge (2002)). More importantly, the censored Tobit analysis enables us to deal with endogeneity issues which are difficult to handle in a duration analysis focusing on hazard functions. In other words, we apply a two-step procedure (procedure 16.1 on page 531, Wooldridge, 2002), which is a standard way to deal with endogenous explanatory variables in censored Tobit models such that the effects of the covariates on the expected duration are estimated correctly.

The Tobit model assumes that, for each random draw i, the log duration $\log(T_i^*)$ given the covariates X_i follows a normal distribution $N(X_i\delta, \sigma^2)$, which implies that T_i^* given X_i has a log-normal distribution, with δ representing the vector of coefficients to be estimated, and σ^2 denoting the variance of the log duration. The hazard function for a log-normally distributed duration, conditional on the covariates, can be written as:

$$\lambda(T_i^*;X_i) = h\left[\left(\log T_i^* - X_i\delta\right)/\sigma\right]/\sigma, \tag{5.6}$$

where $h(z) \equiv \phi(z)/[1 - \Phi(z)]$, $\phi(z)$ is the standard normal density, and $\Phi(z)$ is the standard normal CDF. The lognormal hazard function is not monotonic and does not have the proportional hazard form. Nevertheless, the estimates of δ are easy to interpret because the model is equivalent to:

$$\log\left(T_i^*\right) = X_i\delta + e_i. \tag{5.7}$$

Therefore, δ also represents the semi-elasticities of the expected duration with respect to the covariates.

Suppose we now have one of the variables in the above Tobit model assumed to be endogenous. The model can then be rewritten as follows:

$$\begin{aligned} y &= \max\{0, \log(T_i^*)\}, \\ \log\left(T_i^*\right) &= X_1\delta_1 + \alpha_1 y_2 + u_1, \\ y_2 &= X\delta_2 + v_2 = X_1\delta_{21} + X_2\delta_{22} + v_2, \end{aligned} \tag{5.8}$$

where (u_1,v_2) are normally distributed with zero mean and independent of X. If u_1 and v_2 are correlated, then y_2 is endogenous. The estimation of the above model with an endogenous y_2 can be done correctly using a standard two-step procedure proposed in Wooldridge (2002) (page 531): First, estimate the reduced form of y_2 by OLS, which gives $\hat{\delta}_2$. Define the reduced form OLS residual as $\hat{v}_2 = y_2 - X\hat{\delta}_2$. Second, estimate a standard Tobit of $\log(T_i^*)$ on X_1, y_2 and $\hat{v}_2$. This second step gives consistent estimators of δ_1 and α_1, which identifies the effect of the covariates on the expected duration.

5.3. Identification strategy

There are several potential issues concerning identification that we address as follows.

5.3.1. Direct support versus social learning

There is a potential concern as to whether the social network also has a direct effect on greenhouse adoption through input provision and output marketing services. Fortunately, the social network variable in our empirical study, the number of earlier adopters among relatives and friends, has largely excluded its direct effect of greenhouse adoption because there was no cooperative activity in input purchasing or output marketing among relatives and friends in our study area during the period covered by our survey. To see whether this observation is also reflected in our data, we compare prices of urea, one of the major fertilizers used by farmers and a homogenous product in terms of nutrients and quality, between non-adopters and adopters of greenhouses. The results show that there is no statistically significant difference in urea prices paid by adopters and non-adopters (Table 2, panel C). Moreover, we also include the fertilizer price into the regressions to further control for direct effects from the social network.

5.3.2. Endogeneity issue and its solution

There is a potential endogeneity issue concerning the social learning effect. The issue of endogeneity may arise for reasons discussed in Manski (1993). The latter uses the reflection problem to describe the tendency for people in the same social network to behave in similar ways. He identifies two possibilities: (1) an endogenous effect, wherein the propensity of an individual to

Table 2
Relation between distance to neighborhood and household characteristics.

Panel A: correlations

	Family size (person)	Surname ranking	Age of family head (year)	Total schooling years (year)	Off-farm income (10,000 yuan)
Distance to neighborhood (minute)	0.149	0.042	0.022	−0.048	0.009
	Farm size (mu)	Ratio of construction costs	Distance to road (km)	Distance to market (km)	House value (10,000 yuan)
Distance to neighborhood (minute)	0.042	−0.048	−0.029	−0.040	0.060

Panel B: average household characteristics by distance to neighborhood

Distance to neighborhood	Family size (person)	Surname ranking	Age of family head (year)	Total schooling years	Off-farm income (10,000 yuan)
Below median	3.699	1.736	39.82	7.275	8.51
Above median	4.004	1.995	40.37	6.781	10.87
Distance to neighborhood	Farm size (mu)	Ratio of construction costs	Distance to road (km)	Distance to market (km)	House value (10,000 yuan)
Below median	5.938	2.634	1.144	5.796	5.988
Above median	5.971	2.503	1.153	3.882	7.321

Panel C: fertilizer (urea) price (yuan/kg) across counties

County	Non-adopter	Adopter	Test of equality of the means (p-value)
1	2.074 (0.094)	2.261 (0.141)	0.468
2	2.365 (0.148)	2.276 (0.085)	0.582
3	2.274 (0.195)	2.288 (0.108)	0.955
4	2.158 (0.061)	2.421 (0.251)	0.146
5	2.429 (0.077)	2.618 (0.392)	0.392
6	2.236 (0.123)	2.696 (0.306)	0.490
7	2.249 (0.054)	2.200 (0.043)	0.481
8	2.018 (0.085)	2.168 (0.069)	0.309
9	2.415 (0.229)	2.014 (0.146)	0.701
10	2.584 (0.344)	2.374 (0.096)	0.622
Average	2.248 (0.052)	2.338 (0.057)	0.247

Panel D: Greenhouse construction cost (Yuan) across counties

County	Observations	Mean	Std. Dev.
1	59	9546	5323
2	25	8925	1637
3	37	9553	4581
4	85	7311	2363
5	28	10,993	4000
6	52	11,877	7844
7	82	7995	2231
8	50	10,847	6074
9	24	8626	5376
10	43	11,647	8937
Total	485	9462	5250

Note: Data used in this table is from the field survey described in Section 4.

behave in certain ways varies with the prevalence of the behavior in the group and (2) a correlated effect, wherein a common environment and personal characteristics produce similar behavior.

Here, we focus on testing the hypothesis that farmers' adoption decisions are influenced by social learning. Therefore, we need to empirically distinguish the social learning effect from the endogenous effect and the correlated effect.

In our context, the endogenous effect is essentially the social pressure problem. Psychologists often use the idea of social pressure as a way of explaining “herd behavior.” In Shandong, most farmers are free to make production plans for their own farms after the economic reforms several decades ago. Commonly, farmers in a village have multiple ways of making a living (e.g., farming, off-farm jobs in cities, and small businesses in the village). It seems unlikely that farmers would adopt greenhouse vegetable growing because of social pressure.

In our context, the correlated effect poses a more serious challenge. An endogeneity problem could arise from the simultaneous determination of adoption and network formation: for example, a farmer could know more adopters because he/she built a

Table 3
Greenhouse adoption and social learning: 2SLS versus OLS.
Dependent variable: 1 = adopt, 0 = not adopt.

Explanatory variables	Coefficient (std error)	Coefficient (std error)	Coefficient (std error)	Coefficient (std error)
	2SLS	OLS	2SLS	OLS
Social learning within village	0.032**	0.010***		
	(0.014)	(0.002)		
Social learning within village and nearby villages			0.027**	0.010***
			(0.010)	(0.002)
Market volatility	−0.004***	−0.004***	−0.004***	−0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Conditional mean of market return	−1.241	−1.187	−1.522*	−1.289
	(0.687)	(0.775)	(0.855)	(0.798)
Output price/input price	0.649	1.797**	1.203	1.932**
	(1.381)	(0.860)	(1.381)	(0.850)
Family size (person)	0.007	0.022	0.011	0.022
	(0.025)	(0.022)	(0.023)	(0.022)
Surname ranking	−0.076**	−0.041**	−0.066**	−0.040**
	(0.029)	(0.014)	(0.023)	(0.014)
Age of family head (year)	−0.009***	−0.008***	−0.009***	−0.008***
	(0.003)	(0.002)	(0.003)	(0.002)
Total schooling years (year)	−0.011*	−0.010**	−0.012**	−0.011**
	(0.006)	(0.004)	(0.005)	(0.004)
Off-farm income (10,000 yuan)	−0.006	0.003	−0.003	0.004
	(0.019)	(0.014)	(0.017)	(0.014)
Farm size (mu)	0.008	0.001	0.010	0.001
	(0.013)	(0.011)	(0.012)	(0.011)
Irrigation ratio	−0.086	0.022	−0.024	0.038
	(0.204)	(0.088)	(0.152)	(0.090)
Ratio of construction costs	−0.013	−0.020**	−0.017	−0.021**
	(0.011)	(0.007)	(0.010)	(0.007)
Times of major reallocations	−0.587***	−0.450***	−0.645***	−0.477***
	(0.186)	(0.130)	(0.171)	(0.132)
Years of awareness of the technology (year)	−0.036***	−0.026***	−0.036***	−0.027***
	(0.009)	(0.005)	(0.008)	(0.005)
Greenhouse subsidy (yuan)	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Fertilizer price (yuan/kg)	−0.026	0.009	−0.014	0.011
	(0.053)	(0.019)	(0.041)	(0.018)
Distance to road (km)	0.096	0.143**	0.115*	0.148**
	(0.063)	(0.053)	(0.060)	(0.054)
Dummies and constant terms				
Crop dummy	0.634	0.134	0.473	0.157
	(0.627)	(0.226)	(0.519)	(0.222)
Village dummies	Yes	Yes	Yes	Yes
Constant terms	1.882	0.540	1.361	0.426
	(1.688)	(0.992)	(1.414)	(0.972)
Observations	485	485	485	485
Adjusted R-squared	0.621	0.819	0.685	0.815
Durbin–Wu–Hausman test for endogeneity	*p*-Value	0.044	*p*-Value	0.053

*** denotes significance at 1%, ** 5% and * 10%. Data used in this table is from the field survey described in Section 4.

greenhouse. In other words, the adoption could affect social learning instead of social learning affecting adoption (endogeneity from simultaneous determination). To mitigate this problem, we collected household and institutional information for the year before the adoption of the greenhouse (in the case of adopters). For non-adopters, we collected the information in 2001 (the middle point between 1996 and 2006) (after Carletto et al., 2010).

Moreover, farmers who are entrepreneurial are likely to know more people (hence more adopters). At the same time, they are more likely to try out new things (thus more or less likely to adopt greenhouse, depending on the availability of other options). Therefore, a farmer's adoption could be explained by the farmer's personality, rather than by learning from others in the farmer's social network. Thus, a key problem is how to identify social learning from unobservable error terms such as similar personalities in the social network. We need to find at least one instrumental variable which is (1) correlated with social learning after we control for other factors, but that is (2) not correlated with the error terms. While we can test the first condition, we cannot test the second condition directly because the error terms are not observable.

Fortunately, we have an appropriate instrument: the walking time from the farm to a farmer's neighborhood. More specifically, we ask farmers the following question in the field survey: “How many minutes does it take to walk by your 20 closest neighbors?” The logic of this question is that social learning could be negatively correlated to the walking time. For example, if a farmer lives in a mountainous area, it could take two hours or even more to walk by the farmer's 20 closest neighbors. On the

Table 4
Greenhouse adoption and social learning: first stage 2SLS results.
Dependent variable: social learning.

	Social learning within village	Social learning within village and nearby villages
Explanatory variables	Coefficient (robust std error)	Coefficient (robust std error)
Distance to neighborhood (minute)	−0.078** (0.037)	−0.093** (0.039)
Market volatility	0.011 (0.022)	0.004 (0.024)
Conditional mean of market return	6.212 (28.49)	17.64 (27.54)
Output price/input price	46.79 (46.35)	35.50 (44.06)
Family size (person)	0.930 (0.858)	0.971 (0.842)
Surname ranking	1.722* (0.966)	1.711* (0.966)
Age of family head (year)	0.032 (0.092)	0.026 (0.094)
Total schooling years (year)	0.016 (0.201)	0.065 (0.204)
Off-farm income (10,000 yuan)	0.393 (0.607)	0.347 (0.615)
Farm size (mu)	−0.371 (0.401)	−0.490 (0.397)
Irrigation ratio	5.618 (8.536)	4.445 (7.912)
Ratio of construction costs	−0.342 (0.383)	−0.293 (0.388)
Times of major reallocations	6.118 (6.683)	9.384 (6.388)
Years of awareness of the technology	0.453** (0.233)	0.550** (0.234)
Greenhouse subsidy (yuan)	−0.014 (0.017)	−0.009 (0.017)
Fertilizer price (yuan/kg)	1.524 (1.887)	1.390 (1.852)
Distance to road (km)	2.066 (1.751)	1.764 (1.778)
Dummies and constant terms		
Crop dummy	−10.45 (25.47)	−13.44 (25.70)
Village dummies	Yes	Yes
Constant terms	−55.09 (58.23)	−46.55 (55.47)
Observations	485	485
Adjusted R-squared	0.501	0.528

*** denotes significance at 1%, ** 5% and * 10%. Data used in this table is from the field survey described in Section 4.

contrary, it only takes 10 minutes for farmers to walk by the farmer's 20 closest neighbors if people live close together. We surmise that farmers in the second case are more likely to have access to social learning. We test this hypothesis with data after controlling for other factors: we find that walking time is significantly negatively correlated with social learning (first row of Table 4 for both social learning measures). This result demonstrates that the walking time variable satisfies the first condition for a valid instrument.

For an analysis of whether this instrument meets the second condition (lack of correlation with the error term in the adoption equation), the following discussions provide further justification for the validity of the instrument.

First, we use a heuristic explanation to justify the instrument. In rural China, it is not unusual for a family to live in the same place for decades. A well-functioning real estate market does not exist in rural China for several reasons: (1) a farmer could own a house, but not the land on which the house is built because all land is owned by the village collective; (2) it is illegal to buy a house in a village if the buyer is not a member of the village; (3) it is also illegal for a household to buy an additional house from another villager because Chinese law forbids any household to occupy two pieces of land for housing in a village; and (4) if a farmer wants to change the house location, either he has to obtain a new piece of land from the village collective under very strict conditions due to land scarcity in Shandong, or he can find another household in the village that is willing to give up its housing land, which is very rare. In addition, in both cases the farmer has to give up the old housing land. Based on these observations, it appears very difficult, if not impossible, for a household to change its location. In other words, the farmer's housing location in rural China can be considered as fixed in most cases.

Even though the location of a household appears to be fixed, historically, people who live far away from their neighborhood might also live far away from roads or markets. This suggests that they might have fewer opportunities to learn from markets or from the outside world — an important consideration when analyzing the technology adoption decision. To address this potential concern, we present the correlations between distance to neighborhood and various household characteristics such as distance to roads, distance to markets, education, age, family size, and household wealth proxied by house value. Panel A of Table 2 shows that there is little correlation between distance to neighborhood and the included household characteristics. In panel B, we group the sample households according to whether their distance to the neighborhood is above or below the sample median, and then present the average household characteristics for each group. The results suggest that people who live further away from their neighborhood tend to be richer, and that they are in fact closer to markets. The associated correlations, however, are quite small (see panel A).

As a result of these discussions, we are reasonably confident that the instrumental variable (distance to neighborhood) is exogenous to greenhouse adoption, and therefore it allows us to obtain consistent estimators given that social learning is shown to be endogenous by the Durbin–Wu–Hausman Test (the last row in Table 3).[18]

[18] We also use the Hansen–J over-identification test to examine the validity of the IV. The C-statistics (p-values are 0.25 and 0.28 respectively) indicate that the IV passes the validity test in both social learning measurements. However, we must be cautious by not over-emphasizing this result, as the power of the test depends on the exogeneity of the other instruments (distance to village center) included in the test.

6. Empirical results

In this section we first present the results of the estimation of the linear probability model, and then of the duration analysis.

6.1. Results of estimation of the linear probability model

Table 3 presents the estimation results for the linear probability model estimated by both 2SLS and OLS with cluster-robust standard errors using distance-to-neighborhood as the instrument in the 2SLS. The first two columns report the results using a measure of social learning within the farmer's own village; the next two columns report the results using a measure of social learning that also includes the farmer's nearby villages. Generally speaking, the two sets of results are very similar, suggesting that village boundaries are not crucial to how social learning affects greenhouse adoption.

We will focus on the first two columns for a detailed discussion of our results. The first row confirms the key hypothesis of our study: social learning has a significantly positive impact on greenhouse adoption. Specifically, one more adopter in a farmer's social network increases the probability of the farmer's adoption by about 3.2% after controlling for other factors. In other words, if there are currently 10 earlier adopters in the farmer's social network, the farmer's adoption probability in the next year will increase by about 32%. Given that the greenhouse adoption rate is still low in rural China, this amount of increased probability is economically significant.

The third row shows how adoption is affected by the volatility of the project value, and we use the market volatility of vegetable prices before adoption to represent the uncertainty in the stochastic project value in our theoretical model. The result indicates that this source of uncertainty discourages adoption. This finding is consistent with theory, which predicts that the option value of waiting to invest is larger when the future investment value is more uncertain.

The fourth row shows how adoption is affected by the return to greenhouse use. From our theoretical model, we know that the farmer's belief about the mean return will converge to the average belief of the farmer's social network as a result of social learning. Because we cannot observe farmers' expectations, we use the vegetable price index (national level) growth rate before adoption to approximate the average belief of project return in the social network. The coefficient is not significant; however, the sign is consistent with the prediction of our theoretical model, namely, higher expected returns result in a higher trigger value for investment and a lower probability for adoption. It is also possible that the price index growth rate is acting as a proxy for farmers' outside opportunities; however, we have already included off-farm income in our regression specification.

Our proxy for the current profitability of the greenhouse technology is the ratio of the output price index to the input price index at the provincial level. However, the coefficients are not statistically significant, but the signs are consistent with what the theory predicts.

Among the included household characteristics, the age of the family head and the number of occurrences of major land reallocations are statistically significant, and the results make sense. The older the family head is, the less likely that the person would adopt the technology since greenhouse farming is labor-intensive. More major land reallocations discourage greenhouse adoption because the latter is a long-term irreversible investment facilitated by secure land property rights. The years of awareness of the technology has a negative impact on adoption, suggesting that the likelihood of adoption is smaller conditional on “holding out” for a longer period in the past.

We also include the surname ranking in our empirical model to control for the size of a household's social network. This allows us to rule out the possibility that the adoption decision is driven by the size of the social network, and not by our social learning measure. The result indicates that the size of the social network is negatively related to adoption after we control for social learning, which suggests that a larger social network in the absence of social learning actually discourages adoption. It also helps verify that it is social learning, instead of direct support due to a larger social network, that encourages adoption.[19]

More education, as proxied by a greater number of schooling years in a household, provides family members with more opportunities to run small businesses and take off-farm jobs, and thus discourages greenhouse adoption. The coefficients of off-farm income and the ratio of housing construction cost to greenhouse construction cost are not significant, but the signs are consistent with the descriptive statistics from Table 1.

For comparison, we also present OLS estimation results of the empirical model in Table 3. We find that the social learning effect is still statistically significant. However, the effect is much smaller compared to 2SLS estimation, which suggests that social learning could be negatively correlated with omitted factors in the regression error term. To understand this finding, we note that people who are entrepreneurial in spirit are more likely to have larger social networks and know more prior adopters. At the same time, farmers with an entrepreneurial spirit will consider other possibilities such as starting a small business in the village or migrating to urban areas, which might make it less likely for them to adopt the greenhouse technology. Our finding suggests that we would underestimate the effect of social learning on greenhouse adoption if we fail to control for this endogeneity problem.

A further issue to be noted is that the IV approach may only capture the local average treatment effect (LATE), and LATE is the mean effect on greenhouse adoption for those individuals who benefit from more social learning because the distance to their neighborhood is closer than others. In other words, the estimation results from the IV approach might only reflect the treatment on the compliers: the gains from social learning in rural China likely vary as the distance to their neighborhood changes.

[19] Surname rank one corresponds to the largest surname lineage in the village, and rank two means the second largest surname lineage in the village, and so on.

Table 5
Duration analysis: censored Tobit model (two steps).

	First step: dependent variable		Second step: dependent variable	
	Social learning within village	Social learning within village and nearby villages	Logarithm of waiting time	Logarithm of waiting time
Explanatory variables	Coefficient (std error)	Coefficient (std error)	Coefficient (std error)	Coefficient (std error)
Social learning within village			−0.027* (0.014)	
Social learning within village and nearby villages				−0.023* (0.012)
Market volatility	0.046 (0.029)	0.039 (0.030)	0.003*** (0.001)	0.003*** (0.001)
Conditional mean of market return	−8.256 (29.72)	7.376 (29.58)	−1.195 (0.854)	−0.803 (0.832)
Output price/input price	44.55 (46.70)	29.60 (46.59)	0.222 (1.119)	0.277 (0.962)
Family size (person)	−0.205 (1.233)	−0.226 (1.124)	0.031 (0.029)	0.031 (0.029)
Surname ranking	2.857* (1.523)	2.789* (1.501)	0.011 (0.039)	0.011 (0.035)
Age of family head (year)	−0.101 (0.138)	−0.124 (0.137)	−0.001 (0.003)	−0.001 (0.003)
Total schooling years (year)	−0.186 (0.338)	−0.098 (0.332)	−0.008 (0.008)	−0.005 (0.007)
Off-farm income (10,000 yuan)	−0.409 (0.793)	−0.570 (0.798)	−0.006 (0.023)	−0.009 (0.023)
Farm size (mu)	0.199 (0.635)	0.060 (0.630)	−0.038*** (0.012)	−0.042*** (0.012)
Irrigation ratio	9.626 (11.14)	8.291 (10.39)	0.188 (0.163)	0.124 (0.141)
Ratio of construction costs	0.111 (0.510)	0.134 (0.525)	−0.011 (0.010)	−0.011 (0.010)
Times of major reallocations	8.163 (7.990)	13.50* (7.59)	0.747*** (0.166)	0.844*** (0.206)
Greenhouse subsidy (yuan)	−0.139** (0.044)	−0.128** (0.041)	−0.003 (0.002)	−0.002 (0.002)
Fertilizer price (yuan/kg)	2.604 (3.459)	2.291 (3.404)	0.040 (0.056)	0.024 (0.050)
Distance to road (km)	1.470 (1.835)	0.898 (1.805)	−0.054 (0.068)	−0.072 (0.065)
Distance to neighborhood (minute)	−0.134** (0.062)	−0.154** (0.063)		
Dummies				
Crop dummy	−24.21 (16.96)	−22.61 (17.29)	−0.919 (1.500)	−1.002 (1.502)
Residuals from the first step			0.028** (0.014)	0.026** (0.012)
Village dummies	Yes	Yes	Yes	Yes
Constant terms	−49.96 (58.43)	−38.72 (57.11)	1.562 (1.592)	1.994 (1.480)
Observations[a]	301	301	301	301
(Pseudo) R^2	0.555	0.570	0.343	0.345

*** denotes significance at 1%, ** 5% and * 10%. Data used in this table is from the field survey described in Section 4.

[a] The number of observation decreases from 485 to 301 because the waiting time for some people is zero (either because there is no earlier adopter in their social network (for non-adopters) or they are the first group of adopters (for adopters)), which is not valid for taking logarithm.

The difference between OLS and IV may also be related to this fact. Generally speaking, LATE represents a conditional mean effect of both covariates and treatment while OLS only measures a conditional mean effect of covariates. More importantly, the IV approach might only capture the effect of treatment on a subset of the population (compliers), which is now well known as an important reason why IV estimates tend to be larger than OLS estimates (Wooldridge, 2002). In other words, that the result from the IV approach is larger than OLS might merely reflect the difference between the compliers (those who live closer to their neighborhood and therefore receive more social learning) and the whole population.

A comparison between the two estimation approaches also shows that the ratio of housing and greenhouse construction costs with insignificant coefficients from the 2SLS regression becomes significant in the OLS regression. This is likely due to the potential correlation between this variable and the social learning variable, which is effectively removed by using the distance-to-neighborhood instrument in the 2SLS regression (see Table 2, panel B for the low correlation between the IV and the ratio).

Since the LPM model could predict probability outside the [0,1] interval, we also present the results from Probit and Logit models in Table 6. The results from the Probit/Logit models are quite similar to LPM. The impact of social learning on adoption is still significant in both social learning definitions no matter we use Probit or Logit model. The sizes of social learning impact are close to what we got from 2SLS estimation, which suggests results from 2SLS are more robust. The results for other explanatory variables are also robust in both Probit and Logit model, in some cases, the results of the Probit/Logit model are more significant statistically presumably due to efficiency gains from the MLE.

6.2. Results of the duration analysis

Table 5 presents the estimation results for the censored Tobit model based on the two-step procedure. As theory predicts, social learning reduces the waiting time significantly in both social learning measurements. Since the estimated coefficients are semi-elasticities of the covariates on the expected duration, the result from Table 5 suggests that with one more adopter in the farmer's network, the waiting time of the farmer decreases by about 2–3% (Table 5, column 4 and 5, row 1 and 2). Meanwhile, market volatility increases the waiting time due to the higher trigger value, which is also consistent with both theory and the empirical results in the linear probability model.

As we discussed in the previous section, insecure land property rights discourage adoption and should increase the waiting time. The results in Table 5 confirm those findings. Farm size reduces the waiting time and facilitates adoption, because it is easier

Table 6
Greenhouse adoption and social learning: Probit and Logit models.
Dependent variable: 1 = adopt, 0 = not adopt.

Explanatory variables	Coefficient (std error)	Coefficient (std error)	Coefficient (std error)	Coefficient (std error)
	Probit	Logit	Probit	Logit
Social learning within village	0.030** (0.011)	0.051*** (0.019)		
Social learning within village and nearby villages			0.030** (0.011)	0.050*** (0.018)
Market volatility	−0.021*** (0.003)	−0.041*** (0.008)	−0.022*** (0.003)	−0.042*** (0.008)
Conditional mean of market return	0.259 (3.122)	−1.613 (6.081)	0.336 (3.090)	−1.728 (6.001)
Output price/input price	0.232 (3.344)	3.378 (6.788)	0.322 (3.310)	3.595 (6.723)
Family size (person)	0.097 (0.105)	0.185 (0.211)	0.101 (0.107)	0.184 (0.214)
Surname ranking	−0.124 (0.125)	−0.252 (0.242)	−0.123 (0.125)	−0.250 (0.238)
Age of family head (year)	−0.054*** (0.012)	−0.093*** (0.025)	−0.054*** (0.012)	−0.093*** (0.025)
Total schooling years (year)	−0.038 (0.027)	−0.065 (0.055)	−0.038 (0.027)	−0.065 (0.055)
Off-farm income (10,000 yuan)	0.050 (0.066)	0.116 (0.117)	0.047 (0.067)	0.115 (0.116)
Farm size (mu)	0.043 (0.042)	0.085 (0.079)	0.048 (0.042)	0.093 (0.079)
Irrigation ratio	0.772 (0.522)	1.558 (0.949)	0.778 (0.528)	1.612 (0.950)
Ratio of construction costs	−0.196*** (0.056)	−0.369** (0.106)	−0.200*** (0.056)	−0.372** (0.106)
Times of major reallocations	−0.003 (0.103)	−0.052 (0.128)	−0.015 (0.105)	−0.033 (0.183)
Years of awareness of the technology	−0.067*** (0.023)	−0.123*** (0.045)	−0.072*** (0.024)	−0.131*** (0.047)
Fertilizer price (yuan/kg)	0.007 (0.099)	0.020 (0.155)	0.007 (0.099)	0.019 (0.154)
Distance to road (km)	0.148 (0.095)	0.267** (0.224)	0.154 (0.095)	0.281** (0.222)
Dummies and constant terms				
Crop dummy	0.337 (0.286)	0.496 (0.567)	0.330 (0.287)	0.476 (0.567)
Village dummies	Yes	Yes	Yes	Yes
Constant terms	3.764 (3.360)	3.612 (6.699)	3.620 (3.343)	3.285 (6.660)
Observations	456	456	456	456
Pseudo R-squared	0.503	0.516	0.505	0.517

*** denotes significance at 1%, ** 5% and * 10%. Data used in this table is from the field survey described in Section 4.

for farmers to conduct greenhouse farming if they have enough remaining land to grow grain to feed their family. This is also consistent with the result in Table 3.

As expected, the residuals obtained from the first stage of the two-step estimation procedure are also significant, and the result suggests there is indeed an endogeneity problem in this duration analysis, which is consistent with what the Durbin–Wu–Hausman test has shown in Table 3. Since the first stage of the two-step procedure for the duration analysis is almost the same as the first stage of 2SLS (the only difference being that the year of awareness of technology in Table 4 is removed because it is identical to the dependent variable in the duration analysis), the distance to neighborhood is negatively correlated with social learning, which is also consistent with the results in Table 3.

7. Conclusions

In this paper, we aim at an important gap left by the existing literature, both theoretical and empirical, which has not modeled the effect of social learning in a real option context, particularly with respect to the reduction of uncertainty. We fill this gap by modeling social learning as a way of reducing parameter uncertainty, thus facilitating technology adoption and reducing the waiting time in irreversible investment. We use household-level data from intermediate-technology greenhouse adoption in northern China to test the predictions in both a linear probability model and a duration analysis, with the following main results:

(1) Social learning has a significant positive impact on greenhouse adoption: 10 more adopters in the farmer's social network increase the probability of adoption by 32%, which is an economically significant effect. Moreover, results from the duration analysis confirm this finding through social learning reducing the waiting time significantly in greenhouse adoption.
(2) The empirical results in both the linear probability model and the duration model confirm what we know from the conventional theory of irreversible investment: higher uncertainty about the future investment value results in less likelihood of adoption and longer waiting times.
(3) Insecure land property rights discourage adoption and also increase the waiting time until the irreversible investment is made.

Our paper also provides an answer to a general question: How could small farmers in developing countries deal with the risk from irreversible investment and incomplete information? Our results suggest that social learning can be one effective solution. Therefore, the policy implication from this paper is clear: when small farmers face technology adoptions such as investing in tube wells or machinery, helping several farmers adopt successfully may be the best way to induce more adoption in their village.

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