Individual and Social Learning in Bio-technology Adoption: The Case of GM Corn in the U.S.

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Do-il Yoo
Department of Agricultural and Applied Economics
University of Wisconsin-Madison
dyoo2@wisc.edu

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Do-il Yoo
Department of Agricultural and Applied Economics
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Abstract

Genetically Modified (GM) technology has been widely adopted by the U.S. farmers within just a recent decade since the first generation GM varieties were commercially planted in 1996. Also, it has provided economists with various controversial issues: food safety, biotech industry concentration, labeling regulation, and environmental contamination. In dealing with them, it's the analysis of farmers' technology adoption behaviors that need to be studied fundamentally because it plays a role of the first step to evaluate the associated economic policies and suggest more efficient GM regulations.

The high adoption rates of GM technology are believed to be driven by farmers' expectations for more profitability than planting non-GM (conventional) seeds. In addition, according to the recent improving biotechnologies, the single trait GM seeds of herbicide-tolerant (HT) or insect-resistant (IR) are rapidly substituted by stacked gene varieties. Those trends of tremendous diffusion of GM crops and increasing access to the stacked seeds in such a short history comes with a question about which determinants have influenced farmers' active adoption behaviors under uncertain profitability.

Most of the previous GM adoption literatures have analyzed determinants affecting the diffusion of technology with regards to farmer characteristics such as farm size, education level, risk preference, and credit access. Another recent study pointed out GM crop characteristics represented as average yields, labors, or herbicide/pesticide usages. However, few studies paid attention to the role of externalities in technology adoption decisions; 1) learning process – a process of improving farmers' ability to implement new technology and allowing them to make better decisions. They are composed of individual (learning-by-doing) and social learning (learning from others); 2) neighborhood effects – the tendencies that a farmer's adoption is affected by his/her neighboring farmers' behaviors in a peer group.

These two concepts are worth while to be analyzed empirically in the sense that, in reality, individual technology adoption is affected not only by one's own experiences but also by others' behaviors through continuous social interactions. Also, the learning process requires introducing the dynamic framework into the analysis because farmers' acquired information generates an ability to predict future profitability and leads to the situation that farmers are forward-looking. Therefore, this paper tries to develop a dynamic GM technology adoption model with externalities and explore the importance of learning and neighborhood effects under uncertain profitability.

To the GM technology adoption studies, this paper makes the following contributions: first, externalities of learning and social interactions are directly specified in the empirical model; second, introducing dynamic framework expands the previous limited static level works due to lack of accumulated data in short history of GM technology; finally, the dynamic structural approach can suggest scenario evaluations in terms of various GM issues.

1. Introduction

Genetically Modified (GM) technology provides economists with a variety of issues such as food safety, biotech industry concentration, trade conflicts with labeling regulation, environmental contamination because they keep making globally disputable subjects among researchers. However, prior to dealing with those issues, the fundamental studies about GM technology adoption have not been emphasized so much even though they are the first step to make and evaluate associated economic policies. Especially, the tremendous diffusion of GM technology by the US farmers within just a decade comes with a question about which determinants have influenced farmers' aggressive adoption behavior. In addition, the short history of GM technology results in lack of data, and has limited researchers implement further studies; if ever, most of GM technology adoption papers stay at the level of static analysis without accounting for farmers' virtual forward looking attributes.

This paper analyzes farmers' adoption behavior for GM technology under the dynamic framework which previous works have seldom used. As key determinants of recent rapid technology adoption, this paper focuses on farmers' learning process by their own experience as well as learning from others. Neighborhood effects are also emphasized in terms of social interactions. Learning process and neighborhood effects are interpreted as externalities generated by adoptees, and are thought to affect their future decision making. From these viewpoints, this paper is meaningful in the sense that information and network externalities are specified through the dynamic structural framework of biotechnology adoption.

1.1. Technology Adoption: Learning Process and Neighborhood Effects

The diffusion of new technologies in agricultural sector is believed to increase farm productivity and profitability innovatively. Agricultural technology adoption has been one of the most interesting topics in economics since Griliches (1957) shed light on the analysis of technological innovations with economic processes for the first time.

One branch of studies concerning technology diffusion in agriculture is to explore determinants affecting agricultural technology adoption (Feder et al., 1985; Rogers, 1995; Batz et al., 1999). Rogers (1995) conceptualized these features as relative advantage, compatibility, complexity, trialability, and observability.[1] Those attributes have been embodied through studies on specific characteristics such as farm structure and size (Just et al., 1980), risk and risk preferences (Mansfield, 1966; Feder et al., 1985; Hiebert, 1974; Feder and O'Mara, 1981; 1982), human capital[2] (Barry et al., 1995; Batte and Johnson, 1993), credit constraints (El-Osta and Morehart, 1999), location factors (Green et al., 1996; Thrikawala et al., 1999), and so forth.

In addition to those basic farm characteristics, the importance of learning process and neighborhood effects have been raised as more sophisticated determinants to account for individual farm's adoption behavior about new technologies. They are meaningful in the sense that, in reality, individual decision making is affected not only by one's own but also by others' behaviors through continuous interdependencies.

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[1] The examples of relative advantage are profitability, labor-time saving, cost reduction, and so on. Compatibility and complexity are understood as the similarity with previous technology and the degree of difficulty in experience and use, respectively. Trialability explains how easy experimentation is, and observabiility corresponds to the degree to which the results of technology are visible.

[2] Human capital is represented as operator age, education level, and years of farming experience.

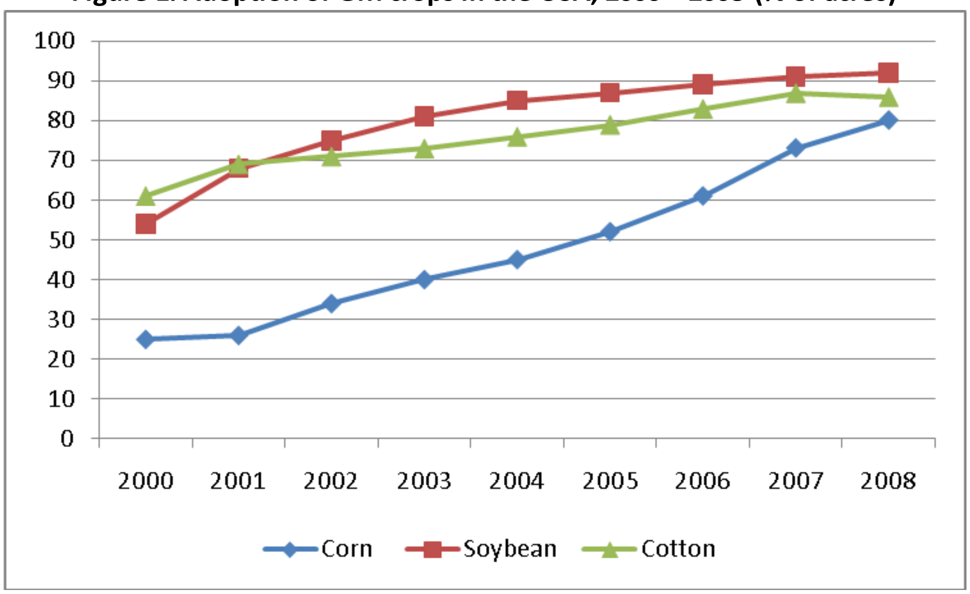
As for learning, Jovanovic and Nyarko (1996) explore one agent's technical choice model concerning the concept of learning-by-doing introduced by Arrow (1962). Further, Foster and Rosenzweig (1995) expand it by incorporating all other agents' choices through the concept of learning from others.

On the other hand, neighborhood effects, defined as social interactions affecting an agent's behavior, have been mainly studied by sociologists (Jencks and Mayer, 1990; Brooks-Gunn et al., 1997; Ellen and Turner, 1997). Their recent moving to economics by the methodological progress in economic theory is yielding various researches from economic aspects (Manski, 2000). Especially, Allen (1982) and An and Kiefer (1995) apply neighborhood effects concept to technology adoption studies.

1.2. Background of Genetically Modified (GM) Varieties

Since the first generation GM varieties were commercially planted in 1996, the U.S. farmers' adoption rate for bio-seeds has kept increasing dramatically (Figure 1). Such a rapid increment is driven by farmers' expectation for higher yields and profitability with lower costs by saving labor and using less herbicide or pesticide (Fernandez-Corncejo and Caswell, 2006).

Figure 1. Adoption of GM crops in the USA, 2000 – 2008 (% of acres)



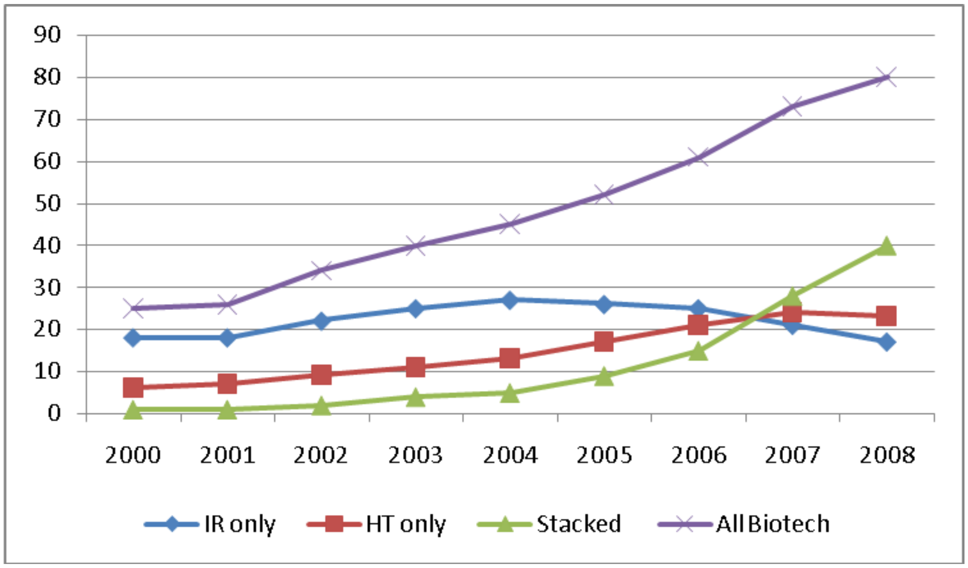
Sources: USDA/NASS Acreage Survey (USDA, 2000, 2002, 2004, 2006, 2008).
Notes: All crops indicate all biotech varieties regardless of traits. Here, cotton is upland cotton.

According to Figure 1, the use of GM cotton grew from 61% of planted all cotton acreage in 2000 to about 86% in 2008, and that of GM soybean also shows similar increase from 54% in 2000 to 92% in 2008. Outstanding rapid increment is shown in the adoption of GM corn from 25% in 2000 to 80% in 2008. Its increment amounts to 55%, whereas those of soybean and cotton during the same period are 38% and 25%, respectively. As such, this paper selects GM corn as a research target in order to see which determinants have driven its most active adoption pattern comparing with other GM crops.

The traits of widely planted GM varieties are herbicide-tolerant (HT) and insect-resistant (IR) traits.[3] In addition, recent improving biotechnologies enhance the use of stacked gene varieties containing both HT and IR traits in a seed. Focusing on GM corn, the growth trend of adopting GM varieties suggests interesting features by traits (Figure 2).

Figure 2. Adoption of GM corn by traits in the USA, 2000 – 2008 (% of acres)

[3] In USDA/NASS data, IR varieties indicate only those containing *bacillus thuringiensis* (Bt).



Sources: USDA/NASS Acreage Survey (USDA, 2000, 2002, 2004, 2006, 2008).
Notes: IR corn includes *bacillus thuringiensis* (Bt) in this data.

While the rate of acreages planting overall GM corn regardless of traits (all biotech seed) keeps increasing, individual GM corn seeds show various evolution trends by their traits. The adoption rate of IR (Bt) corn peaked at 25% in 2004, but it kept decreasing ever since, arriving at an even lower level of about 16% in 2008 than 19% in 2000. As for HT corn, though its use shows a similarity to that of all biotech corn with steady growth, it fell down slightly from 23% in 2007 to 22% in 2008 by about 1%. In the years to come, it seems to be potentially downward like the case of IR corn. In contrast to single trait corn varieties, stacked gene corn variety shows a rapid growth tendency; its planted acreage rate was at only 1.67% in 2000. However, the adoption expands at an increasing rate after a slow start, and amounts to 44.22% in 2008. These statistical changes are explaining farmers' GM trait adoption choices are switching to multiple stacked trait seeds from the single trait seeds in earlier times.

Further, considering some market circumstances associated with GM corn supplements what this paper analyzes. First, it's notable that the market structure of the GM seed industry is highly concentrated through frequent consolidations among biotech-seed companies (Ollinger and Fernandez-Cornejo, 1995; Fernandez-Cornejo, 2003). This fact raises a question about linkage between industry concentration and technological change. For example, if a few biotech seed companies exercise market power, farmers may not adopt GM seeds so much due to higher cost. Second, GM technology is facing controversial issues concerning environment or food security, which can hinder farmers from adopting GM technology owing to export contraction in trade with EU or Asian countries enforcing GMOs labeling regulations (Dohlman et al., 2000). The environment or security topic about GMOs is not restricted only to trade cases, but is applied to the domestic transactions in the U.S; while the U.S. consumers' attitudes for GMOs have been even more positive than EU or Asian consumers', the food safety issue is in trend of arousing the U.S. consumers' concerns about GMOs. As an example, since Mendocino County in California banned GM products in March 2004 in the U.S. for the first time, bans are currently effective in Marin, Santa Crutz, and Trinity Counties, and are still spreading across other counties in California (Larson, 2008). This shows that spreading regulation for GMOs due to food safety may impede consumers' purchases of GMOs and may restrain farmers' adoption of GM technologies in the long run. Third, the recent interests in corn-ethanol biofuel are expected to accelerate corn farmers' adoption of GM varieties due to expected higher yields.

1.3. The Object and Motivation of Research

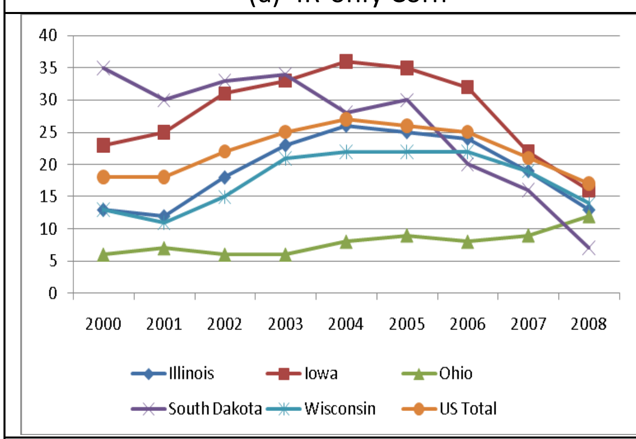
Associated with the current circumstances of GM corn varieties previously described, the objective of this paper is to explore the U.S. corn farmers' GM technology adoption behaviors in terms of learning process and neighborhood effects. For this research, the dynamic structural model is introduced with a panel data of the U.S. corn farmers.

For several motivations, this GM technology adoption study is meaningful. First, a lot of technology adoption studies since Griliches (1957) have been performed on various kinds of fields, whereas GM technology is seldom focused on as much as other agricultural technologies. In addition, though a few previous empirical works about GM crops have analyzed determinants affecting the diffusion of technology with regards to farm size (Fernandez-Cornejo et al., 2001), risk preferences (Alexander et al., 2003), or GM product characteristics (Useche et al., 2005), few studies paid attention to the role of farmers' learning or neighborhood effects in the diffusion process.

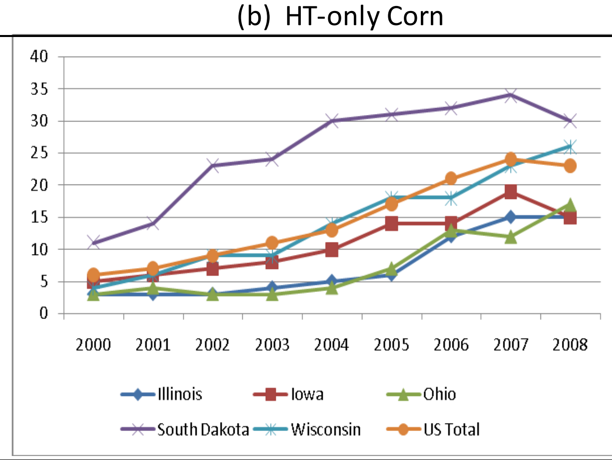
Second, using panel data in this paper suggests an incentive to deal with the information acquisition and intertemporal interactions among agents which used to be difficult in the static approach. To this time, relatively short history of GM technology lets relevant empirical works focus on cross-sectional studies due to lack of accumulated data. Though Fernandez-Cornejo et al. (2002) introduces a dynamic approach based on a logistic model with time-series data in examining diffusion, it is limited in dynamic process panel data could capture (Besley and Case, 1993). Third, there exists an apparent spatial heterogeneity in the US GM corn (Figure 3), which answers the question of why this paper focuses on analyzing adoption behaviors; the different growth trends of GM corn by states are related to Griliches' (1957) demonstration that the diffusion of new technologies results from a series of developments taking place at different rates across geographical regions. Further, in terms of individuals' strategic behaviors, it provides a rationale of introducing learning spillover and neighborhood effects in the sense that the spatial diffusion is associated with the spread of knowledge about the innovation (Lindner and Pardey, 1979; Marra et al., 2003).

Figure 3. Adoption of GM corn both by traits and states in the USA, 2000 – 2008 (% of acres)

(a) IR-only Corn

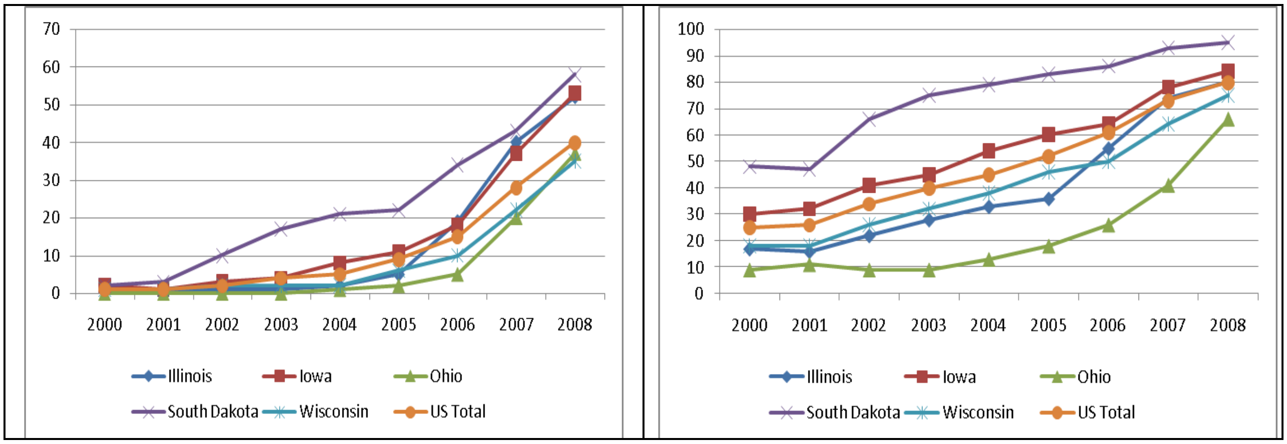


(b) HT-only Corn



(c) Stacked Gene Corn

(d) All Biotech Corn



Sources: USDA/NASS Acreage Survey (USDA, 2000, 2002, 2004, 2006, 2008).
Notes: IR only corn includes only *bacillus thuringiensis* (Bt) in this data.

2. Literature Review

2.1. Empirical Literatures on GM Technology Adoption

Though the GM technology is an attractive issue as it has brought revolutionary changes in agricultural field in terms of production as well as cost sides, the empirical analyses for its adoption behaviors have been conducted relatively less than other kinds of agricultural technology. Such insufficient research activities result from lack of accumulated data in short history of commercial GM varieties.

At this stage, empirical studies concerning GM technology have taken notice of determinants affecting GM crop adoption focusing on individual farm level characteristics. For one thing, Fernandez-Cornezo et al. (2001) show that larger farm operations and more educated farmers increase the usage of HT soybeans through the tobit model, considering farm size and farmer's education level as crucial determinants. However, using cross-section data is limited in capturing dynamic structure potentially existing in those determinants.

For another thing, risk preferences are mainly analyzed under the common idea that farmers are likely to exhibit risk aversion to income risk, which affects technology adoption. Alexander et al. (2003) reports risk preferences influence the decision to plant GM corn but not soybeans. Qaim and Janvry (2003) analyze Bt cotton adoption under a monopoly pricing regime by gathering farmers' willingness to pay data. Recently, Liu (2008) argues more risk averse farmers adopt Bt cotton later. All those risk relevant works are based on the surveyed cross-sectional data asking WTP to respondents,[4] which also neglect dynamic process aspects.

As for a dynamic approach, Fernandez-Cornejo et al. (2002) explore determinants of the diffusion rates of GM corn, soybean, and cotton by developing a diffusion model, modified version of Griliches' (1957) logistic function. However, they are closer to a time series approach rather than a panel data method. Also, the term of "dynamic" used originates from the setup of diffusion path parameters as time-varying ones, but is distinguished from the commonly used term of dynamic programming (DP).

Most recently, Useche et al. (2005) analyze the adoption of GM crop at the upper Midwest in the U.S. Their work is very close to this study in that it selects GM corn as a research target, and investigates farmers' adoption behavior in terms of specific GM corn traits such as HT, IR, and stacked genes. Also, Useche et al. expand the traditional logic of a random utility framework (Marschack, 1960; McFadden

[4] Due to the absence of WTP in the dataset of this paper, risk preference is little focused on.

and Train, 2000) based on independence of irrelevant alternatives to the characteristics-based demand approach (Revelt and Train, 1998; Nevo, 2000; 2001) which allows substitution among alternatives. Methodologically, mixed multinomial logit model is applied for dealing with those logics. In spite of close association with this paper, Useche et al. have limits in focusing on a static analysis based on the cross-sectional data without incorporating dynamics. Also, under the absence of dynamics, their work is not sufficient to account for farmers' learning process which is specifically described in the following section.

2.2. Literatures on Technology Adoption with Learning and Neighborhood Effects

2.2.1. Literatures on Technology Adoption

Agricultural technology adoption studies have been emphasized on the introduction. The researches about technology diffusion are studied mainly in developing countries because technological progress is recognized as a key to relive farmers' poverties. Measuring the diffusion of new technologies from economic perspectives is available only if a certain period of time passes. Therefore, corresponding studies require the framework of dynamics. In addition, geographical difference is also considered because the spread of new agricultural technology varies according to agro-ecological states in each region (Griliches, 1957). That is to say, temporal and spatial heterogeneity make a basis for technology adoption studies.

Recent technology adoption model is based on the choice theory and related microeconomic theories. In addition, farmers' behaviors surrounding technology adoption are interpreted through viewpoints of externalities. Besley and Case (1993) stress the importance of externalities in making empirical adoption models specifying them as network or neighborhood, market power, and learning externalities.[5] Learning and neighborhood effects which this paper takes into account are understood under those externalities concepts.

2.2.2. Literatures on Technology Adoption – Learning Process

Learning is evaluated as a process of improving farmers' ability to implement new technology and allowing them to make better decisions. Bardhan and Udry (1999) categorize learning process as the following two concepts: learning-by-doing and learning from others. As learning-by-doing deals with an individual's own information acquisition in an isolated situation, it is thought to be simpler than the analysis including learning from others. Those concepts related to learning process are addressed by Lidner et al. (1979) in earlier times. Stoneman (1981) introduced a Bayesian theory in investigating a typical sigmoid diffusion curve. The Bayesian approach is effective in representing agents' activities for information acquisition as the feature of learning process is exactly consistent with the Bayes' sense; agents update information from subjective prior beliefs into posteriors.

Learning from others improves learning-by-doing by incorporating interactions with other agents. In agriculture, learning-by-doing is realized by farmers' own experiments such as testing new seeds, spraying new agrichemicals, or purchasing new combines. However, self experiments without referring to others' experience may impede the diffusion of new technologies because a farming cycle is generally long term; as for most of yearly crops, farmers can judge a new technology only after a year goes by. So that, learning process can be accelerated by obtaining information from neighboring farmers (Bardhan and Udry, 1999). As learning from others contains other agents' behaviors in one's decision making, it accompanies studies concerning agents' strategic behaviors. Yet, the interpretation about agents' strategic behaviors suffers from its ambiguity; for example, when there are positive externalities from

[5] Network externalities are understood as public goods; an agent's adoption choice is influenced by how many other agents adopt it because technology plays a role of public goods. Market power externalities provide the logic of first- and second- mover advantage under the existence of market power. Learning externalities is related to the concept of free riding; e. g., potential adopters wait until they see whether others benefit from experiencing adopted technologies.

information provided by many farmers in a newly introduced technology, potential adopters have an incentive to adopt it as early as possible. On the contrary, if farmers want to wait and observe how well new technologies work by other farmers, this kind of strategic delay forms a free-rider problem (Kapur, 1995; McFadden and Train, 1996; Vives, 1997).

In empirical dynamic models for learning process, farmers have been set up as not only forward-looking but also strategic agents. Forward-looking features are specified through the Bayesian updating procedure concerning posterior distributions about beliefs. Also, externalities occurring at future period let models include the form of present-discounted value. Strategic feature results from agents' interactions described previously (Baerenklau, 2005). As a result, economists have designed strategic dynamic model (Manski, 1993; Bolton and Hariis, 1999), and Besley and Case (1994) laid groundwork for that. They set up a Bellman equation of the profit maximization problem for Indian farmers choosing whether to adopt high-yielding seed varieties (HYVs) as a new technology. In this DP, a stochastic state equation is designed, where the law of motion comes from a farmer's beliefs evolution following Bayes' rule. For capturing strategic behaviors, all other farmers' adoption choices are included in each farmer's policy function.

While most of technology adoption literatures rely on the Bayesian theorem for its tractability, it should not be fully supported if only researchers want to avoid the unrealistic information updating process. The reason why the Bayesian models are vulnerable is that accompanied assumptions are too strong to reflect reality in analysis; it starts from the presumption that agents know all associated variances, which is unlikely fashion. On the other hand, Epstein and Schneider (2007) provides the generalized version of Bayes' rules by allowing agents to have confidence in profitability assessment, and by introducing the importance of risk and ambiguity in learning process.[6]

As another branch for dealing with learning spillover, the target-input model[7] comes into wide use since Foster and Rosenzweig (1995) analyzed social learning relevant to adoption decision with same data of HYVs technology in India. Its idea is from the model setup that an agent's profit decreases with the square of the distance between his actually used input level and the unknown optimal, called as 'target', input level. Here, his information acquisition is explained as a process of deducing what the target input level must have been after the output is realized through learning by doing and learning from others.[8] Though it has provided economists an advantage of simplifying adoption model with respect to social learning, it is vulnerable by its strong assumption: the new technology is always superior[9], and is known with certainty when he decides his input decision. In addition, the profitability from that technology keeps increasing as his knowledge accumulates (Bardhan and Udry, 1999). That is to say, if this assumption is applied to this paper, GM technology is supposed to be adopted with certainty, whereas the only uncertainty lies in a farmer's input management; how well he makes use of GM seeds in order to reach the optimal input level as close as possible.

However, in reality, a farmer's adoption behavior for new technologies is a process with uncertainty by itself because the adoption decision may affect his profitability directly (Besely and Case, 1994; Baerenklau, 2005). Besley and Case begin with the assumption that profit is uncertain and exogenous,

[6] However, the Bayesian updating is still adopted by this paper because of its tractability. Instead, the concept of learning under ambiguity is left out for the future work.

[7] It's developed by Prescott (1972) for the first time. Jovanovic and Nyako (1994) used the model in analyzing information acquisition and its effects on the productivity change.

[8] Foster and Rosenzweig (1995) or Bardhan and Udry (1999) are recommended for more details.

[9] This assumption prevents economists from accounting for disadoption of a technology.

where it's uncertain to farmers whether the adoption of new technology is good or not, so a new technology is not always adopted by them. For example, even though farmers adopt GM technology in earlier times, they may go back to planting non-GM varieties if they put environmental issues related to potential gene contamination in the long run before instant advantages from GM technology in the short run. As well, farmers trying to get higher profitability from organic crops may not necessarily adopt GM technology. Neither do those who plant non-GM crops for exporting to countries that GM labeling regulation is rigorous. As a result, Besley and Case's approach, based on the assumption of uncertain profitability from adoption, is more appropriate for this paper than that of Foster and Rosenzweig in order to reflect more realistic situations concerning current commercial GM corn seeds.

2.2.3. Literatures on Technology Adoption – Neighborhood Effects

Neighborhood effects are interpreted as kinds of externalities that an agent's behavior is affected by all other agents' behaviors in a cohort defined as a neighborhood group. They look similar to social learning, especially the concept of learning from others. However, it's distinguished from social learning in the sense that an agent's choice is affected not by others' process but by contemporaneous others' choices themselves.[10]

While Besley and Case (1994) and Foster and Rosenzweig (1995) have enriched social learning studies, neighborhood effects are not yet explored so much as learning process though they are on a same path with regards to agents' interactions. Instead, neighborhood effects have been studied by social scientists in other fields such as sociology, education, geography, and so forth. Jencks and Mayer (1990) and Durlauf (2004) provide a historical review for them.

The recent application of economic theories to neighborhood effects are stimulating related economists (Manski, 2000; Brock and Durlauf, 2001a, 2001b, 2002). Yet, they still suffer from identification problem in econometric methodologies (Manski, 1993). As for technology adoption studies, Allen (1982) examines adoption behaviors under network externalities restrictive to local neighborhoods with statistical mechanics models. An and Kiefer (1995) explores which conditions derive more efficient technologies adopted and adoption timing. As for technology adoption in agriculture, Case (1992) analyzes a case of sickle adoption in rural Indonesia, presenting the absence of neighborhood effects bias estimation of parameters. Recently, as for Wisconsin dairy farmers' management intensive rotational grazing (MIRG) technology adoption, Baerenklau (2005) incorporates neighborhood effects into a strategic dynamic model with other two key determinants: risk preference and learning. It also suggests that ignoring neighborhood effects causes bias in estimation in spite of its less relevance than other factors.

This paper adopts Baerenklau's methodology in analyzing neighborhood effects.[11] It sets up the neighborhood effect term as a function of the deviation from the average behavior by a farmer's neighborhood group suggested by Brock and Durlauf (2001), and incorporates the Bellman equation in a multi-period but non-dynamic setting. Except for the incorporation of risk preference, Baerenklau's work is similar to this paper in the sense that it analyzes technology adoption with respect to not only learning process but also neighborhood effects at the same time. As Baerenklau's analysis results from small size data with 34 observations, this paper expects improved evidence concerning learning and neighborhood spillovers by using larger panel data set.

3. Model

[10] For example, under social learning, one's technology adoption is affected by others profitability caused by adoption (indirectly). Yet, in neighborhood effects, one's adoption is affected by others' adoption itself (directly).

[11] Also, Baerenklau (2005) supports Besley and Case (1994) rather than Foster and Rosenzweig (1995) due to the same reason described in Section 2.2.2.

3.1. Theoretical Model – Dynamic Structural Model

As described in the previous section, this study relies on Besley and Case (1994) in terms of farmers' forward looking behavior and Bayesian learning process for technology adoption under the dynamic structure. In part, neighborhood effects are also considered by referring to Baerenklau (2005).

Those two studies are distinctive in the choice of models concerning the tractability of estimation: the reduced-form versus the structural model. As for adoption behavior, Baerenklau depends on the reduced form model as it is tractable for estimation with relative ease. Though the suitability of estimation attracts researchers to use it, specifying an exact functional form of the decision rule from a dynamic optimization problem is not such an easy procedure; the reduced form estimation is vulnerable as it tends to obscure the dynamic context of estimation, and to misinterpret coefficient estimates in a dynamic environment. In addition, as the estimated parameters change in any policy variation unlike the structural model, it's not useful for evaluating policy associated with interesting environmental changes such as price promotion, changed market structure, or the introduction of new commercial technology (Provencher, 1997).

On the other hand, as Besley and Case adopt the structural dynamic model of Pakes (1986) and Rust (1987), the structural model can be used as an alternative for the reduced-form model including the evaluation of policy. However, estimating the structural model accompanies high dimensional integrations in solving the dynamic optimization problem not only at all values of the state space but also on all possible alternative choices.[12] As a result, to reduce the size of the choice set or the state space has been implemented in the dynamic structural estimation studies. Those efforts result in having focused on extremely simplified representations of dynamic process for the dichotomous decisions; e.g., whether to adopt or not a new technology. But, as for GM technology in this paper, a farmer's adoption decision is not simply restricted to the binary choice of GM vs. non-GM seeds. Despite its computational burden, it's necessary to expand its logic to a multinomial discrete choice model for the more realistic analysis concerning GM traits: conventional (non-GM), HT, IR, and other kinds of stacked seeds.[13]

At the same time, another choice variable characterizing the extent to which a selected technology is applied is also required to reflect agents' learning process; it's explained by the assumption that the information acquisition for a newly adopted technology is represented as how many fields a specific GM trait seed is sown to. Therefore, through this paper it's meaningful to develop a further dynamic structural model for considering combined choices of which technology to adopt and how much to apply the selected one.[14]

3.1.1. The Basic Setup - Dynamic Optimization Problem

The theoretical explanation begins with setting up a typical dynamic choice problem. Under the uncertainty of new technologies, farmer i maximizes the present expected value of future payoff flows. As for choice variables in his optimization problem, in each period he makes adoption decisions in two ways; he decides which technology to adopt and how much to apply it. A similar issue is dealt with in the exit-investment decision (Pakes, 1994) and the brand-quantity choice of inventory goods (Hendel and Nevo, 2006) problems, but their choice variables are assumed to be decided separately; optimal discrete choice is followed by the quantity choice. Assuming consumers' utility is decided at the timing of brand

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[12] This computational burden is named as "curse of dimensionality" by Bellman (1957).

[13] As for used terms, a specific GM trait is called as an alternative or choice a farmer chooses. Also, each trait (alternative) can be considered as one of new technologies through from this section on. Therefore, trait, choice, alternative, and technology are used interchangeably.

[14] This approach is called as the mixed continuous discrete controls model by Pakes (1994).

choice, Hendel and Nevo's approach provides computational simplicity by considering brand choice as a static problem. However, it seems to be rather unlikely because it's more reasonable that utility is also affected by how much they consume simultaneously; i.e., quantity choice (Erdem et al., 2003). Therefore, this paper assumes that farmers' adoption and application choices are assumed to be decided at the same time.

Suppose that there are $L+1$ possible alternatives which farmer i can choose for each finite time period t. Alternatives are assumed to be mutually exclusive, and indexed by $l = 0, 1, \dots, L$, where $l = 0$ denotes an outside alternative.[15] Though farmers tend to adopt multiple technologies at a decision period, it's assumed that they adopt one alternative in each period for simplicity.[16] Defining d_{ilt} as his adoption choice for alternative l at time t, his adoption decision for technology l is described as $d_{ilt} = 1$, otherwise $d_{ilt} = 0$ by assuming $\sum_{l} d_{ilt} = 1$. In addition, it's denoted as x_{ilt} how much the adopted technology is used in his field. Specifically, it's expressed as the acres which trait l seed is sown to given farmer i has X_i fields. While the technology adoption behavior d_{ilt} is a discrete variable, x_{ilt} is understood as a continuous variable where $x_{ilt} \in [0, X_i]$. Though it's ideal x_{ilt} belongs to a continuous set, it may be discretized arbitrary for empirical tractability; that is indexed by $x_{ilt} \in \mathbf{X}_{ilt}$, wherer $\mathbf{X}_{ilt}$ is an arbitrary discrete set[17]. Uncertainty of any new technology is represented as the assumption that farmers are uncertain about profitability obtained from any adopted specific GM trait.

Letting I_{it} be the information set which farmer i receives at time t, I_{it} includes all state variables affecting current expected utilities and the distribution of the future expected utilities. A farmer's current period expected utility from each technology is marked as $E[U_{ilt} \mid I_{it}]$ where $E[\cdot]$ indicates the expectation operator.[18] To deal with the application amount of the adopted technology l, the expected utility is assumed to be additive, so that it's proportional to the acres sown with the chosen GM trait seed. Given $E[U_{ilt} \mid I_{it}]$ indicates the expected utility per acre and farmer i sows trait l seeds to x_{ilt} acres at time t, the total expected utility amounts to $x_{ilt} \cdot E[U_{ilt} \mid I_{it}]$. Through these setups, farmer i makes an optimal sequence of adoption and quantity decision $\{d_{ilt}, x_{ilt}\}_{l \in L+1}$ for $t = 0, \dots, T$ in order to maximize his discounted-present value of the expected utility of

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[15] In this paper, the choice of $l = 0$ indicates the use of non-GM (conventional) seed. From this section on, unless it's denoted as $l = 0$, index l indicates $l = 1, \dots, L$.

[16] This assumption doesn't seem to be realistic as farmers tend to purchase various GM trait seeds including conventional seeds in each period, so that this paper can't capture economies of scope by multiple adoptions. However, to avoid computational burden, this paper simplifies potential combinations into exclusive $L+1$ choices.

[17] For example, $x_{ilt} \in \mathbf{X}_{ilt}$ = {0%, 20% and less, …, 100% and less}. See Section 3.2.2. for further explanation.

[18] Instead of the term "utility", "profit" may be more appropriate from the viewpoint of the production theory that farmers are producers. However, farmers are also considered as consumers in the sense that their adoption behaviors for any GM technology correspond to purchasing kinds of products (commercial GM seeds). Moderately, a farmer's profit or payoff is in common use with his utility. Its specific form is shown in Section 3.1.3.

$$V_{it}(I_{it}) = \max_{(\{d_{ilt}\}_{l\in L+1}, x_{ilt}\in \mathbf{X}_{ilt})} E\left[\sum_{\tau=t}^{T} \gamma^{\tau-t} \sum_{l\in L+1; x_{il\tau}\in \mathbf{X}_{il\tau}} d_{il\tau}\cdot x_{il\tau}\cdot E\left[U_{il\tau} \mid I_{i\tau}\right] \mid I_{it}\right] \tag{1}$$

where $V_{it}(I_{it})$ is farmer i's value function at time t depending on his current information set I_{it}. Defining $V_{ilt}(I_{it})$ as the alternative l specific expected value function, (1) is expressed alternatively as

$$V_{it}(I_{it}) = E_{e_{it}}\left[\max_{\{d_{ilt}, x_{ilt}\}} V_{ilt}(I_{it}) + e_{it}(\{d_{ilt}, x_{ilt}\})\right] \tag{2}$$

, where $e_{it}(\{d_{ilt}, x_{ilt}\})$ is a stochastic term known to farmers but unobserved by the researcher. This stochastic term is used for forming choice probabilities in Section 3.1.4.2., so that it's assumed to be independently and identically distributed (i.i.d.) the type I extreme value distribution. Then the corresponding Bellman equation for each alternative specific value function $V_{ilt}(I_{it})$ at $t = 0,\ldots, T-1$ is

$$V_{ilt}(I_{it}) = \max_{\{d_{ilt}, x_{ilt}\}}\left\{x_{ilt}\cdot E\left[U_{ilt} \mid I_{it}\right] + \delta E\left[V_{it+1}(I_{it+1}) \mid I_{it}, \{d_{ilt}=1, x_{ilt}\}\right]\right\} \tag{3}$$

where δ indicates the discount factor. At the last period T, the alternative-specific value function is simply $V_{ilT}(I_{iT}) = \max_{\{d_{ilT}, x_{ilT}\}}\left\{x_{ilT}\cdot E\left[U_{ilT} \mid I_{iT}\right]\right\}$ as there are no more future values. In (3), the second expectation operator at the value function in the following period is taken over the distribution of I_{it+1} conditional on I_{it} and the current choice combination $\{d_{ilt}=1, x_{ilt}\}$.

Equation (3) shows the value farmer i attains from adopting technology l is decided by the current expected utility as well as by the discounted future value based on the future information set. His adoption choice updates the information set just as learning about technology profitability is provided by his experience. From the viewpoints of this information acquisition process, it makes senses that he can obtain a higher expected maximum utility as he acquires more information about profitability provided by newly adopted technologies. Therefore, $V_{it}(I_{it})$ is thought to increase as more information is accumulated in the information set I_{it}.

3.1.2. Dynamic Optimization Problem with Externalities

Next, it's necessary to note that one of the research objectives is to analyze learning process and neighborhood effects as determinants for the adoption model. Those concepts are interpreted as information and network externalities which affect technology adoption decisions, respectively (Besley and Case, 1993). As such, the Bellman equation in (2) and (3) need to be developed by including additional terms which can account for those externalities; this paper would be meaningful in the sense that it's an empirical work of internalizing externalities into the model directly.

Learning Process

Learning externalities are represented as a kind of public good which a farmer shares with his neighbors by learning-by-doing and learning from others over time. They are associated with a dynamic framework in terms of the state transition function between I_{it} and I_{it+1} in (3), which is simply described by a conditional distribution function $F_t(I_{it+1} \mid I_{it})$. Under the idea that farmer i's knowledge about the adopted technology for alternative l is considered as a public good, the conditional distribution function depends not only on his own decision but also on all other neighbors' decisions, so that it is modified as[19]

$$F_t(I_{it+1} \mid I_{it}, \{d_{ilt}=1, x_{ilt}\}, \{d_{-ilt}=1, x_{-ilt}\}) \tag{4}$$

[19] For simplicity, Equation (4) is assumed to follow a Markov process which the current states are influenced by just the previous period states not by their histories.

where the subscript $-i$ indicates all neighbors excluding farmer i in a peer group. The combinations of $\{d_{ilt}=1, x_{ilt}\}$ and $\{d_{-ilt}=1, x_{-ilt}\}$ implies farmer i's and all other neighbors' adoption decisions at time period t, respectively. Therefore (4) provides the process of evolution in terms of information acquisition through time, and the concepts of learning-by-doing and learning from others can be captured by components of $\{d_{ilt}=1, x_{ilt}\}$ and $\{d_{-ilt}=1, x_{-ilt}\}$, respectively. The functional specification for (4) is dealt with in Section 3.1.4.1.

Neighborhood Effects

Following Section 2.2.3., neighborhood effects are interpreted as kinds of network externalities that a farmer's decision is affected by all other neighbors' choices in a peer group. Neighborhood effects and social learning (learning from others) look similar each other, but this paper distinguishes them in the sense that only learning process plays a role of the state equation in the DP. On the other hand, neighborhood effects are believed to affect one's contemporaneous choice rather than his future behavior when they are modeled in the DP (Case, 1992).

Let's denote N_{it} as a neighborhood group which farmer i belongs to at time t, and n_{it} be the total number of neighbors in that peer group. Following Brock and Durlauf (2001; 2002), neighborhood effects are assumed to show up through the deviation for a farmer's choice from the mean choice level of his neighbors in that group.

Then, learning process in (4) and neighborhood effects are introduced in the Bellman equation given in (2) and (3). The DP with externalities are expressed as

$$V_{it}(I_{it},\{d_{-it}, x_{-it}\}) = E_{e_{it}}\left[\max_{\{d_{ilt}, x_{ilt}\}} V_{ilt}(I_{it},\{d_{-ilt}=1, x_{-ilt}\}) + e_{it}(\{d_{ilt}, x_{ilt}\})\right] \tag{5}$$

where the alternative-specific expected value function is

$$V_{ilt}(I_{it},\{d_{-ilt}=1, x_{-ilt}\}) = \max_{\{d_{ilt}, x_{ilt}\}}\left\{\begin{array}{l} x_{ilt}\cdot E\left[U_{ilt}\mid I_{it}\right] \\ \\ +\eta\cdot\left(\left(\mathbf{1}\{d_{ilt}=1\}\cdot x_{ilt}\right)-\dfrac{1}{n_{it}-1}\sum_{j\neq i}\left(\mathbf{1}\{d_{jlt}=1\}\cdot x_{jlt}\right)\right)^2 \\ \\ +\delta E\left[V_{it+1}(I_{it+1},\{d_{-it+1}, x_{-it+1}\})\mid I_{it},\{d_{ilt}=1, x_{ilt}\},\{d_{-ilt}=1, x_{-ilt}\}\right] \end{array}\right\} \tag{6}$$

The newly added term in (6) is composed of a parameter to be estimated η, and the square of the deviation from the mean choice level by farmer i's neighbors. $\mathbf{1}\{\cdot\}$ is the mathematical indicator function operator. Then, for each neighbor $j\neq i$ in N_{it}, the acres sown with GM trait l seeds, $\mathbf{1}\{d_{jlt}=1\}\cdot x_{jlt}$, are interpreted as the extent to which each neighboring farmer applies the adopted technology l at time t. The sigma term divided by the number of neighbors in the peer group describes the mean value of all other neighbors' adoption levels for technology l. The measurement of η depends on the situation a farmer is facing; if farmer i's adoption extent for alternative l is less than the average level of the neighborhood, it's interpreted as the case he suffers from a utility loss by the late technology adoption when η is negative. On the other hand, when η is positive, it's interpreted as his strategic behavior because he benefits from a utility gain by waiting and seeing neighbors' profitability of adopting alternative l technology (Baerenklau, 2005).

The newly added term in Equations (5) and (6), $\{d_{-ilt}=1, x_{-ilt}\}$ are accounting for influences by learning externalities, especially the context of learning from others. The expectation operator is taken over the distribution of $F_t(\cdot)$ given in (4).[20] The expansion of the value functions constructs the situation that farmer i's adoption decisions generate information that is a public good, which is modeled by letting the conditional distribution function depend on all other neighbors' adoption decisions. That is, each farmer obtains information about technology profitability not only from his own experience but also from other neighbors' sowing experiences.

3.1.3. Farmer Expected Utility[21]

This section specifies farmer i's expected utility function given in the modified dynamic optimization problem in (5) and (6). In consumer decision making studies, the multi-attribute utility theory (MAUT) is widely used because it provides useful tools for evaluating and comparing alternatives which consumers are facing in their choice problems (Lancaster, 1966). Provided the profitability obtained from any GM trait seed is understood as one of its attributes under MAUT, farmer i's utility is assumed to have the following expression:

$$U_{ilt} = w_p P_{ilt} + w_Y Y_{Eilt} + w_Y r Y_{Eilt}^2 + e_{ilt} + \Gamma' z_i + \alpha_{il} + u_t \tag{7}$$

where U_{ilt} is farmer i's per unit alternative-specific utility[22] conditional on the adoption of technology l at time t, and P_{ilt} is the price he pays for that technology. Y_{Eilt} indicates the experienced (perceived) profitability levels from technology l where subscript "E" denotes "experienced" (the further explanation is described below). e_{ilt} is the random shock associated with farmer i and technology l at time t. Regardless of which technology is adopted, z_i represents a vector of all other farmer-specific attributes affecting utility, which is invariant over time. Whereas α_{il} is an unobservable farmer- and technology-specific component which is also time-invariant. This component corresponds to unobservable heterogeneity which is observable to farmers but unobserved by the econometrician. Generally, a probability distribution function is given for α_{il} because it has randomness. Due to its importance in estimation, it will be described further in the below subsection. The last term u_t is a year-specific shock common to all farmers like weather states, and is assumed to follow an i.i.d. normal distribution of $N(0, \sigma_u^2)$.

As for parameters to be estimated, w_p and w_Y show farmer i's price response coefficient and profitability weight, respectively. Γ is a vector of parameters to account for farmer-specific factor z_i. In addition, r is the farmer risk coefficient. Given a strictly positive w_Y, $r > 0$, $r = 0$, or $r < 0$ lets the utility function be convex, linear, and concave in Y_{Eilt}, respectively. As far as the experienced profitability Y_{Eilt} is uncertain, the previous logic also shows that the farmer is risk seeking, risk neutral, or risk averse with respect to $r > 0$, $r = 0$, or $r < 0$, respectively (Erdem and Keane, 1996).[23]

In the given utility function, two components suggest interesting issues: Y_{Eilt} and P_{ilt}. The former is associated with learning process which constitutes the majority of this paper, and the latter is relevant

[20] In terms of Equation (4), the last term in (6) is expressed as $\delta \int V_{it+1}(I_{it+1}, \{d_{-it+1}, x_{-it+1}\}) dF_t(I_{it+1} | I_{it}, \{d_{ilt}=1, x_{ilt}\}, \{d_{-ilt}=1, x_{-ilt}\})$

[21] Due to similarity of problem setups, most of logics are based on Erdem and Keane (1996).

[22] In empirical part, "per unit" indicates "per discretized acreage", which depends on how x_{ilt} is defined.

[23] Though the given utility functional form suggests a risk analysis, this paper assigns more weights on the analysis of learning and neighborhood effects.

to the context of market concentration in the biotechnology seed industry. The logic is based on an idea that each farmer's adoption behavior may be affected by biotech seed companies' market exercise power in the highly concentrated industry. It's reasonable the increment of P_{ilt} reflects that of market concentration in biotech seed industry (Shi et al., 2008). Then, estimated price weight w_p is interpreted as a response to the change in market concentration partially.

Whereas, in acquiring information, Y_{Eilt} is associated with beliefs about new technologies and plays a role of measuring the varied profitability from technology adoption (Besley and Case, 1994). Due to farmers' uncertainty about technology profitability, each farmer is imperfectly informed and uncertain about the mean profitability levels for each technology. As Besley and Case assume that using a new technology generates the intrinsic advantage, it's assumed that the adopted technology l yields the profitability which varies around its mean level but isn't perfectly perceived. Letting Y_{ilt} be the actual profitability from which farmer i adopts technology l at time t, the variation in profitability is expressed as

$$Y_{ilt} = Y_l + \xi_{ilt} \tag{8}$$

where Y_l is the mean profitability level for technology l, and ξ_{ilt} is the error term causing variability. ξ_{ilt} is assumed to be an i.i.d. random variable with zero mean and a variance. In obtaining information of the profitability from technology adoption, farmers hardly get perfect information from their experience in realizing the actual profitability level Y_{ilt}; for example, if a farmer who planted GM crops suffers losses by a sudden weather shock like a flood in the harvesting period, his experienced (perceived) profitability level $Y_{E_{ilt}}$ is not the same as the actual level Y_{ilt} received just before that incident. As such, it's obvious that there exists inconsistency between the experienced (perceived) profitability level $Y_{E_{ilt}}$ and the actually received level Y_{ilt} from the adopted technology for each farmer at any period, which is expressed as

$$Y_{Eilt} = Y_{ilt} + \zeta_{ilt} \tag{9}$$

where ζ_{ilt} is an i.i.d. random disturbance with mean zero. Then, from (8) and (9), the information learned by adopting a technology can be rewritten as

$$Y_{Eilt} = Y_l + v_{ilt} \tag{10}$$

where $v_{ilt} = \xi_{ilt} + \zeta_{ilt}$.[24] Equation (10) shows that a farmer's experience of profitability from the adopted technology l fluctuates around its mean profitability level.

Unobservable Heterogeneity

In addition to the uncertainty of technology profitability, there also exist unobservable variables to the econometrician, which are defined as unobservable heterogeneity. It's well known that, if they are not modeled with panel data, the identification of parameters is infeasible because the endogeneity problem occurs between observable explanatory variables and error component (Wooldridge, 2002). In a static model, such endogeneity problems can be dealt with typical random or fixed effect approaches. However, the learning model in this paper requires alternative methodologies due to its dynamic framework. As for the dynamic discrete choice model with panel data, Honore and Kyriazidou (2000) and Chintagunta et al. (2001) provide useful tools identifying parameters with unobservable

[24] Though it's not empirically tractable to separate ξ_{ilt} and η_{ilt}, the error term v_{ilt} in (10) moderately provides the variability of farmer experiences with the profitability levels for each adopted technology.

heterogeneity as well as lagged dependent variables. But, their works are focused on a binary choice problem, so that it's necessary to expand them to the multivariate choice case adjusted for this paper. More importantly, their works are limited in the assumption of state independence even though this paper has to deal with the case of state correlation which exists in the context of perception error, and affects choice probabilities associated with the likelihood function for estimation.

Specifically, concerning learning process and neighborhood effects in this study, unobservable heterogeneity to the econometrician includes farmers' cognitive ability, education level, and the intensity of communications between neighbors. The ideal way for treating those components is to find corresponding instrument variables, but it's not easy to find them empirically. Instead, this paper assumes that the farmer- and technology- specific invariant component α_{il} captures all associated unobservable variables, and is incorporated additively in the utility model as in Equation (7). In addition, it is assumed to be correlated with other components affecting a farmer's utility, and the conditional probability distribution for α_{il} is given as $f(\alpha_{il} \mid P_{ilt}, Y_{Eilt}, Y_{Eilt}^2, z_i) \equiv f(\alpha_{il} \mid \tilde{I}_{it})$ where $\tilde{I}_{it} \subset I_{it}$ and i.i.d. to other error terms u_t and e_{ilt}. The given probability measure will be used in constructing choice probabilities and likelihood function for parameter estimates.

For simplicity, α_{il} is assumed to be modeled only in the utility not in the state transition equation. In this sense, α_{il} is not a state variable because its artificial value is realized at the beginning and is invariant over time. While education level is satisfying this assumption, it seems to be a strong assumption for the case of farmers' cognitive ability or the intensity of communication among neighbors as they may be different at each time period. Then, a more realistic assumption will be modeling unobservable components in the state transition equation. But, that equation is already composed of unobservable uncertainties about farmers' profitability, so that there will be potential computational burdens if learning process is modeled with unobservable heterogeneity, together.[25]

Turning back to (7), the expected utility associated with technology l conditional on the information set at time t is derived by taking expectation in Equation (7) as follows:[26]

$$E\left[U_{ilt} \mid I_{it}\right] = w_p P_{lt} + w_Y E\left[Y_{Eilt} \mid I_{it}\right] + w_Y r\left(E\left[Y_{Eilt} \mid I_{it}\right]\right)^2 + w_Y r E\left[\left(Y_{Eilt} - E\left[Y_{Eilt} \mid I_{it}\right]\right)^2\right]$$
$$+\Gamma' z_i + \int \alpha_{il} f(\alpha_{il} \mid \tilde{I}_{it}) d\alpha_{il} + e_{ilt} \tag{11}$$

where e_{ilt} is the disturbance component unknown to the researchers.[27] As for the outside alternative of $l = 0$ such as non-GM trait (conventional) seed, its expected utility is simply suggested as

$$E\left[U_{i0t}\right] = U_{i0t} = \omega_0 + \kappa_0 t + \alpha_{i0} + e_{i0t} \tag{12}$$

where ω_0 and κ_0 are intercept and a coefficient for time trend, respectively. α_{i0} accounts for unobservable heterogeneity for non-adoption case. This setup for conventional seed is more realistic in

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[25] Therefore, this issue is left for the future work.

[26] It's necessary to understand why the expected utility in (11) is used instead of utility itself in (7); farmer i has uncertainty about the technology, and the derived utility from its adoption is not known with certainty. Therefore, empirical analysis must be based not on utility but on the expected utility model.

[27] The error term is remained just for notational clearance. As it's the same error term in Equation (2) and (5), it can be ignored in Equation (11).

the sense that farmers also learn about profitability from conventional seeds. It's assumed that time trend reflects such increment in the expected utility. For simplicity, it can be normalized to zero like Besley and Case.

3.1.4. Learning Process

3.1.4.1. Bayesian Updating

Based on the Bayes' theorem,[28] this section tries to specify the conditional distribution function suggested in Equation (4). Equation (10), the linkage between a farmer's perceived profitability and the mean profitability level for each technology, plays a crucial role in constructing the relevant functional form. Assuming farmers are Bayesian updaters, learning process is interpreted as a trial that farmer i receives an experience (perceived) signal Y_{Eilt} about the mean profitability level Y_l with signal noise v_{ilt} when he adopts technology l at time t, and updates his prior beliefs by using those information over time in the Bayesian fashion.

Recalling Equation (10), let's assume that the mean profitability level of technology l, Y_l is unknown to farmer i at time t, but that he has priors for it. For computational simplicity, his prior subjective beliefs on Y_l and the signal noise v_{ilt} are assumed to follow normal distributions at any time period t when technology l is considered to be adopted. Then, beliefs are expressed as the first two moments of the normal distribution; the mean and variance. Specifically, both distributions are shown as

$$Y_l \sim N(Y_t, \sigma^2_{Yilt}), \qquad v_{ilt} \sim N(0, \sigma^2_v) \tag{13}$$

where σ^2_{Yilt} is the variance as well as the extent of uncertainty about Y_l at time t, whereas Y_t indicates the average level about Y_l at time period t. The average level can be expressed as $E[Y_l \mid I_{it}] = Y_t$ under farmer i's information set at period t. Holding those prior beliefs, he updates his prior distribution into posterior distribution under the Bayes' rule. If this updating process starts from the initial period, (13) can be rewritten in terms of $t = 0$ as $Y_l \sim N(Y_0, \sigma^2_{Yil0})$, where Y_0 and σ^2_{Yil0} imply the initial mean value and the initial variance about Y_l.

At time period t, farmer i decides to adopt technology l among $L+1$ alternatives. At the same time, he also considers the extent of adoption application; how many acres to apply the adopted GM trait seed. Then, his choice variables are a combination of d_{ilt} and x_{ilt}. In addition, by the structure of Equation (4), $F_t(\cdot)$ should incorporate other neighboring farmers' choice combinations, d_{-ilt} and x_{-ilt} in its functional form. By incorporating other farmers' adoption decisions, not only a farmer's own experience (learning-by-doing) but also social learning (learning from others) can be considered together.

Empirically, when the Bayesian rule is applied to problems with the assumptions of normal distributions, the associated updating formula is somehow simplified through Kalman filtering (Besley and Case, 1994; Erdem and Keane, 1996; DeGroot, 1970).

Let's assume that there are n_{it} farmers in an arbitrary neighbor group N_{it} which farmer i belongs to. Conditional on the adopted technology l by farmer i, he gets information about that technology over time by his own experience, and learns how profitable the technology is by observing other neighbors'

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[28] As mentioned previously in Section 2.2.2., the strong assumptions of knowing variances in the Bayesian manner may cause unrealistic interpretation about the analysis (Epstein and Schneider, 2007), but this paper follows conventional approaches most of adoption studies have utilized due to tractability, leaving alternative model setups of learning ambiguity as future works.

farming. The basic idea for empirical procedure is that the learning process is represented as the variation in the selected type of GM trait and the planted acreage over years. Denoting X_{lt} by the total acres which technology l is applied in the group N_{it} at time t, the following expression holds:

$$X_{lt} \equiv x_{ilt} + \sum_{j \neq i} x_{jlt} = \sum_{i=1}^{n_{it}} x_{ilt} \tag{14}$$

Then, by the logics described previously and Bayesian updating procedure, his learning process concerning the mean about Y_l is expressed as[29]

$$E[Y_l \mid I_{it}] = E[Y_l \mid I_{it-1}] + \mathbf{1}\{d_{ilt} = 1\} \cdot \sigma^2_{Yilt} \cdot \left(\sigma^2_{Yilt} + \sigma^2_v + \frac{\sigma^2_{Yilt}}{d_{ilt} \cdot x_{ilt} + \sum_{j \neq i} d_{jlt} \cdot x_{jlt}} \right)^{-1} \cdot \left(Y_{Eilt} - E[Y_{Eilt} \mid I_{it-1}] \right) \tag{15}$$

where $\mathbf{1}\{\cdot\}$ is the indicator function operator, σ^2_{Yilt} is the variance of a farmer's perception of the mean profitability level of technology l. Then, Equation (15) includes components accounting for both learning-by-doing and learning from others (social learning) by incorporating his own and others' adoption extent x_{ilt} and x_{-ilt}. In other words, all neighbors' experiences are used in updating a farmer's information about the mean profitability of any technology by assuming that farmers' information gain by experience is represented as the extent of technology application; acres sown with biotech seeds. For example, given all terms are positive and ceteris paribus, the more all farmers' adoption experiences denoted as X_{lt} are, the higher his next period average level about the mean profitability of the selected technology is; in this process, he obtains information from his own and all other neighbors' sowing experiences. In addition, the deviation of Y_{Eilt} from $E[Y_{Eilt} \mid I_{it-1}]$ in the last term also accounts for a farmer's information acquisition process partially. If farmer i 's perceived profitability of technology l is higher than the mean profitability, that is $Y_{Eilt} > E[Y_{Eilt} \mid I_{it-1}]$, he will revise upward his estimate of the mean profitability for next period, but revise it downward otherwise. Equation (15) is expressed more explicitly in terms of Kalman gain coefficients as follows:

$$E[Y_l \mid I_{it}] = E[Y_l \mid I_{it-1}] + \beta_{ilt} \cdot \mathbf{1}\{d_{ilt} = 1\} \cdot \left(Y_{Eilt} - E[Y_{Eilt} \mid I_{it-1}] \right) \tag{16}$$

$$\beta_{ilt} = \frac{\sigma^2_{Yilt}}{\left(\sigma^2_{Yilt} + \sigma^2_v + \frac{\sigma^2_{Yilt}}{d_{ilt} \cdot x_{ilt} + \sum_{j \neq i} d_{jlt} \cdot x_{jlt}} \right)} \tag{17}$$

, where β_{ilt} is the technology l -specific Kalman gain coefficient which is a function of perceived variance σ^2_{Yilt} and experience variability σ^2_v. Then, the coefficient β_{ilt} measures the weight level farmer i assigns in updating his information about the mean profitability of technology. As σ^2_{Yilt} is updated at each time, β_{ilt} is also updated.

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[29] For further derivation of the equation, it's recommended to refer to Besley and Case (1994) or Erdem and Keane (1996).

In the sense that σ^2_{Yilt}, the variation about Y_l, shows farmers' extent of uncertainty about a specific technology l, it's also meaningful to provide the updating rule for the variance. Following the Bayesian rules with normal distribution assumptions, the difference equation, conditional on technology l is adopted, between the current period variance σ^2_{Yilt} and the following period variance σ^2_{Yilt+1} about Y_l is derived as follows:[30]

$$\sigma^2_{Yilt+1} = \frac{(\sigma^2_{Yilt} + \sigma^2_{v} \cdot X_{lt})}{1 + \left(1 + \dfrac{\sigma^2_{v}}{\sigma^2_{Yilt}}\right) \cdot X_{lt}} \tag{18}$$

where X_{lt} stands for the application quantity of adopted technology.

In Equation (16), a farmer's perception error is defined as $\varepsilon_{ilt} = E\left[Y_l \mid I_{ilt}\right] - Y_l$, and its variance is denoted by σ^2_{Yilt} (Erdem and Keane, 1996). Then, Equation (16) can be rewritten as the following transition equation with regards to the perception error:

$$\varepsilon_{ilt} = \varepsilon_{ilt-1} + \beta_{ilt} \cdot \mathbf{1}\{d_{ilt} = 1\} \cdot \left(v_{ilt} - \varepsilon_{ilt-1}\right) \tag{19}$$

Finally, Equations (15) ~ (19) are used to construct the specified functional form of Equation (4) which plays a role of the state transition equation (the law of motion) in the dynamic optimization problem in (5) and (6). Assuming the Markov process, and focusing on the relation between Y_t and Y_{t+1}, which are the mean levels in prior beliefs about the mean profitability of technology l, Y_l, the conditional distribution function $F_t(I_{it+1} \mid I_{it}, \{d_{ilt} = 1, x_{ilt}\}, \{d_{-ilt} = 1, x_{-ilt}\})$ in (4) is specified by providing the distribution of Y_{t+1} conditional on Y_t as follows[31]

$$Y_{t+1} \mid Y_t \sim N\left(Y_t, Var(Y_{t+1} \mid Y_t)\right) \tag{20}$$

From the viewpoint of learning process, it's necessary to separate two distinctive models to analyze how farmers' information acquisition affects their technology adoption behaviors. The typical method is to distinguish the standard dynamic optimization problem in two ways according to whether the future value function term is included or not: if it includes those components, the model is called as the "forward-looking" model in the sense that farmers make adoption decisions with the consideration of potential future utility by learning process (Besley and Case, 1994; Erdem and Keane, 1996). On the other hand, if farmers want to maximize only their current utility from any technology adoption ignoring possible future utilities, the value functions from the next period on are eliminated in their optimization problem. This model is defined as "myopia" by Besley and Case, and "immediate utility maximization" by Erdem and Keane.[32] Those two models are easily distinguished just by setting discount factor δ is equal to zero in the related dynamic optimization models between (1) and (6).

3.1.4.2. Choice Probabilities

Constructing choice probabilities is crucial in the estimation strategy as they are used in generating likelihood functions. As there are a lot of unobservable factors, it's necessary to take integrals over all

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[30] The derivation may be wrong as it has a different structure with what's shown at p15 in Besley and Case (1994).

[31] Following Besley and Case (1994) and DeGroot (1970), $Var(Y_{t+1} \mid Y_t) = \left(X_{lt}^{3}\left(X_{lt}\sigma^2_{Yilt} + \sigma^2_{v}\right)\left(\sigma^2_{Yilt}\right)^2\right) \cdot \left\{\left(X_{lt}\sigma^2_{Yilt} + \sigma^2_{Yilt} + X_{lt}\sigma^2_{v}\right)^2\right\}^{-1}$ is derived, which may be derived wrongly.

[32] This paper calls it the "myopia" model as Besley and Case did.

relevant randomness. A key randomness comes from unobservable (to the econometrician) heterogeneity in Section 3.1.3. and serial correlation of farmers' perception error in Section 3.1.4.1.

Again, assuming that the error terms e_{ilt} and e_{i0t} in Equations (5), (11) and (12) are assumed to be i.i.d. the type I extreme value distribution, the choice probability that farmer i adopts any GM technology and its planting acreage combination is constructed with regards to the multinomial logit model. As it's explained in the previous section, it's meaningful to distinguish the myopia from the forward-looking model for investigating learning effect.

For notational simplicity, the choice probability for the myopia model is described first. Given the information set I_{it}, the probability that the combination of technology l and quantity x is adopted at time t is

$$\Pr(\{d_{ilt} = 1, x_{ilt}\} \mid I_{it}) = \int_{\varepsilon}\int_{A} \frac{\exp\left(x_{ilt} \cdot R\left[U_{ilt} \mid I_{it}\right] + x_{ilt} \cdot A_{il} + \eta N_{ilt}\right)}{\sum_{k=0,\ldots,L;\, x_{ikt} \in \mathbf{X}_{ik}} \exp\left(x_{ikt} \cdot R\left[U_{ikt} \mid I_{it}\right] + x_{ikt} \cdot A_{ik} + \eta N_{ikt}\right)} F(A)\, g(\varepsilon)\, dA\, d\varepsilon \tag{21}$$

where $R\left[U_{ilt} \mid I_{it}\right]$ is the deterministic part in the expected utility in (15), and A_{il} represents the term including unobservable heterogeneity with a given probability $F(A)$.[33] ε implies a random variable of the perception error in (19) with a given probability distribution $g(\varepsilon)$. Another component ηN_{ilt} is added to the deterministic expected utility, which captures the neighborhood effects in farmers' contemporaneous adoption choices. Specifically, ηN_{ilt} is the squared deviation terms between one's and others' technology – quantity combination choices in Equation (6). It can be interpreted as the measure of how different neighbors adopt the same technology with a farmer (Brock and Durlauf, 2002).[34] Treating Equation (21) is computationally problematic as both the perception error ε and unobservable heterogeneity term A is unobservable to the econometrician. As such, the choice probability should be set up as integrals over any distribution of possible ε and A spaces. The estimation for this setup is possible by adopting simulation techniques to integrate out the ε and A, such as Monte Carlo simulation (Keane and Wolpin, 1994).

The overall logic is similarly applied to the forward-looking dynamic model. That is, the choice probability that technology l adopted with the acreage (quantity) x at time t conditional on the information set I_{it} and other farmers' choices $\{d_{-ilt}, x_{-ilt}\}$ is described as

[33] $A_{il} \equiv \int \alpha_{il} f(\alpha_{il} \mid \tilde{I}_{it})\, d\alpha_{il}$ from Equation (11).

[34] The setup of this paper is slightly different from Brock and Durlauf (2002), where, instead of the deviation concept, they use the agent's expectation of the percentage of agents in the neighborhood who make the same choice p_{ilt}, where $p_{ilt} = (1/n_{it}) \cdot \sum_{i=1}^{n_{it}} \mathbf{1}\{d_{ilt} = 1\}$, in the choice probabilities of $\Pr(d_{ilt} = 1) = \int_{\varepsilon} \frac{\exp\left(R\left[U_{ilt} \mid I_{it}\right] + \beta p_{ilt}\right)}{\sum_{k=0}^{L} \exp\left(R\left[U_{ikt} \mid I_{it}\right] + \beta p_{ikt}\right)} g(\varepsilon)\, d\varepsilon$.

$$\Pr(\{d_{ilt}=1, x_{ilt}\} \mid I_{it}, \{d_{-ilt}=1, x_{-ilt}\}) =$$

$$\int_{\varepsilon}\int_{A} \frac{\exp\left(\begin{array}{l} x_{ilt}\cdot R\left[U_{ilt} \mid I_{it}\right] + x_{ilt}\cdot A_{il} + \eta N_{ilt} \\ + \delta E \left[\begin{array}{l} V_{it+1}(I_{it+1}, \{d_{-it+1}, x_{-it+1}\}) \\ \mid I_{it}, \{d_{ilt}=1, x_{ilt}\}, \{d_{-ilt}=1, x_{-ilt}\} \end{array} \right] \end{array} \right)}{\sum_{k=0,\dots,L;\, x_{ikt}\in \mathbf{X}_{ik}} \exp\left(\begin{array}{l} x_{ikt}\cdot R\left[U_{ikt} \mid I_{it}\right] + x_{ikt}\cdot A_{ik} + \eta N_{ikt} \\ + \delta E \left[\begin{array}{l} V_{it+1}(I_{it+1}, \{d_{-it+1}, x_{-it+1}\}) \\ \mid I_{it}, \{d_{ikt}=1, x_{-ikt}\}, \{d_{-ikt}=1, x_{-ikt}\} \end{array} \right] \end{array} \right)} F(A)\, g(\varepsilon)\, dA\, d\varepsilon \qquad (22)$$

From Equation (6), the corresponding choice probabilities are influenced not only by the current deterministic expected utility from adopting technology l with quantity x , but also by the future utilities under the effects of his own experience and what he learns from others. The only difference between (21) and (22) is the setup of the discount factor δ =0. The neighborhood effects term is also incorporated. Then, another setup of η =0 for neighborhood effects enables researchers to analyze the impact of neighborhood effects by comparing how different the one with the neighborhood effect terms is from the other without them.

3.2. Empirical Implementation

3.2.1. Data

This paper uses a panel data about GM corn varieties between 2000 and 2007 in the U.S. national level. From supply sides, it's a high quality data set because all GM trait information is included, and information at biotech seed company level is available with prices. However, it is not strongly enough for the technology adoption studies in some senses; first, it doesn't include farm level attribute variables such as household income, education level, farm assets, or farm credits. As those variables are thought to affect farmers' GM seeds adoption behaviors, this paper may try to combine demographic information from other agricultural census, which may cause a potential inconsistency in estimation. In addition, the absence of input data like herbicide or insecticide use may restrict further analysis; all kinds of GM traits like HT or IR is associated with input uses.

Table 1. Observations by Sequential Planting Years

Period	Sequential Years	Number of Panel Observations
2003 ~ 2007	5 years	103
2004 ~ 2007	4 years	102
2005 ~ 2007	3 years	245
2006 ~ 2007	2 years	1,016

Useche et al. (2005) solve the similar problem by adopting US Agricultural Census information.[35] Though this data has 168,862 observations, this paper faces a huge data loss in utilizing them because all the observations do not satisfy panel characteristics. Through 8 years between 2000 and 2007, only 175 among 38,617 farmers show up in every year; its ratio is just 0.45%. Further, focuses on neighborhood

[35] This is one reason this paper relies on MAUT, which doesn't emphasize on farm level attributes so much by its utility function structure.

effects may cause more data loss because the narrower the sample group is selected at County or State level from national level, the smaller the number of panel observation is.[36]

Table 2. Distribution of Observations over Region and Sequential Years

2003 ~ 2007			2004 ~ 2007			2005 ~ 2007			2006 ~ 2007		
State	CRD	Obs.	State	CRD	Obs.	State	CRD	Obs.	State	CRD	Obs.
Illinois	17020	3	Illinois	17010	4	California	6051	2	California	6051	3
Illinois	17060	3	Illinois	17070	2	Illinois	17010	4	Colorado	8060	8
	…			…			…			…	
Minnesota	27050	2	Michigan	26090	2	Iowa	19010	11	Illinois	17080	12
Minnesota	27070	2	Minnesota	27040	2	Iowa	19020	3	Illinois	17090	7
Minnesota	27080	4	Minnesota	27050	6	Iowa	19030	6	Indiana	18010	2
Minnesota	27090	3	Minnesota	27070	2	Iowa	19040	3	Indiana	18020	12
Nebraska	31030	2	Minnesota	27080	2	Iowa	19050	5	Indiana	18030	12
Nebraska	31060	7	Minnesota	27090	4	Iowa	19060	2	Indiana	18040	2
	…			…			…			…	
	…			…			….			…	
South Dakota	46090	2	Ohio	39030	2	Kansas	20070	4	Iowa	19010	16
Wisconsin	55060	2	South Dakota	46030	2	Kansas	20090	3	Iowa	19020	16
Wisconsin	55070	3	Wisconsin	55060	2	Kentucky	21020	2	Iowa	19030	19
	Total:	68		Total:	74		Total:	192		Total:	971

In defining a neighborhood group, this paper assumes a crop reporting district (CRD) corresponds to a peer group; though a CRD covers a huge area geographically, it's a reasonable assumption because a CRD is inherently arranged according to the same agronomic conditions. Investigating the panel data set preliminary, this section suggests a few samples satisfying research objects. Table 1 presents the number of panel observations by a few sequential planting years.

In addition, a neighborhood group is further defined as a CRD which has at least 2 more observations. Then, corresponding regional distribution is shown up in Table 2.

Finally, this paper simplifies various GM corn varieties into 5 alternatives by their GM traits: conventional, HT, IR, HTIR, and IRIR. This classification may vary flexibly according to sub topics of the research. For example, stacked GM seeds can be segmented into double, triple, quadruple stacked seeds.

3.2.2. Empirical Specification

Table 3. Classification of the Associated Variables

Notation	**Definition**	**Description**
Choice Variables		
d_{ilt}	Trait choice	Binary choice variable: 0 or 1
l =0	Conventional	Non-GM corn seeds
l =1	HT only	Single trait GM corn seeds; Herbicide Tolerance
l =2	IR only	Single trait GM corn seeds; Insect Resistance
l =3	HTIR	Double stacked GM corn seeds; HT + IR
l =4	IRIR	Double stacked GM corn seeds; IR + IR

[36] Despite its small observations at narrower sectors, this paper avoids the national level analysis because the definition of a neighborhood is nonsense if the whole U.S. corn farmers are dealt with.

x_{ilt}	Acres	Acres to be planted with corn seeds
$x_{ilt} \in \mathbf{X}_{ilt}$	$\mathbf{X}_{ilt}$ = { 0%, 20% and less, 40% and less, 60% and less, 80% and less, 100% and less}	Discretized planted acreage choices.
State Variables		
I_{it}	Information Set	All associated state variables or other kinds of components are included in the information set.
P_{ilt}	Corn Seed Price	Retail price or net price
N_{it}	Neighborhood group	Crop Reporting District (CRD)
n_{it}	Number of Neighbors	CRD level
d_{-ilt}	Trait choice of a neighbor	Binary choice variable: 0 or 1 by neighbors
x_{-ilt}	Acres of a neighbor	Acres to be planted with corn seeds by neighbors The setup is the same as x_{ilt}
z_i	Farm specific Variables	The vector of all variables related to farmers e.g.) Acre Range, Intended End Use, Purchase Source, Possible demographic data from other source
D_{ilt}	Discount Price	The amount of discounted price

All the variables associated with the given dynamic optimization problem in Section 3.1.2 are described in Table 3. For time period t, the empirical work chooses 3 survey years from 2005 through 2007 considering moderate number of panel observations. At each time t, there are totally 5 possible GM/non-GM technology adoption choices indexed by l for a corn farmer at one neighborhood group (CRD): $l = 0$ indicates non-adoption by choosing conventional seed, and the other non-zero integers denote currently commercialized single (HT or IR) and stacked (HTIR or IRIR) trait seeds, respectively (Table 3). Then, farmer i's choice variables are which GM trait to adopt and how many acres to plant purchased GM corn seeds. For empirical tractability of the DP, the planted acreage x_{ilt} is recommended to be discretized instead of being treated as a continuous variable. Initially, it's discretized as 6 indecies of x_{ilt} corresponding to 0%, 20% and less, 40% and less, …, 100% and less, respectively with regards to the ordered range of planted acre percentage for each trait seed.[37]

Table 4. Parameters to be Estimated

Notation	Definition	Description
The Expected Utility		
w_p	The Price Weights	
w_Y	The Utility Weights	Or the profitability weights

[37] Of course, this classification is arbitrary, and it can be recalibrated flexibly: e.g., it can be ramified by 10%, 5%, or 1% level for a more detailed analysis.

r	Risk Parameter	
Γ	Other parameters	Related to z_i
Neighborhood Effects		
η	Neighborhood Effects	
Dynamic Optimization Model		
δ	Discount Factor	At myopia, δ =0
Learning Process		
Y_l	The Mean Technology Profitability	l is GM traits
σ^2_{Yil0}	Initial Perceived Variance	At initial value t =0
σ^2_v	Experience Variance	
Others		
ω_0	Intercept	For $l = 0$
κ_0	Time Trend Response	For $l = 0$

The parameters to be estimated in the dynamic structural model are shown in Table 4. This paper focuses on farmers' learning process based on the Bayesian theorem, so that parameters related with the Bayesian updating are worth being noted carefully; Y_l , σ^2_{Yil0} , σ^2_v for l =1,…,4.

4. Model Estimation

Though the dynamic structural model in Equations (5) and (6) are similar to Erdem and Keane (1996)'s brand choice model, estimating parameters shown in Table 4 will be such challenging works due to the following reasons: first, our model has two dimensional choices of one binary and the other continuous (in fact, descretized) variables. Hendel and Nevo (2006) and Erdem et al. (2003) deal with similar setups in storable or inventory goods, but their value functions have different structures from ours. Second, as state variables, this model incorporates other agents' decision variables in order to capture social interactions of learning from others and neighborhood effects. This case corresponds to the Markov Perfect Equilibria (MPE) game between agents. Those two subjects are incorporated in our model at the same time, so that it'll be challenging to develop appropriate estimation methodology. Third, first of all, modeling unobservable heterogeneity and serial correlation demands a lot of endeavors to solve the DP. Due to its computational burden, only the outline is described in this section.

4.1. Solving the DP

As a starting point, this section introduces Keane and Wolpin (1994)'s simulation and interpolation algorithm which is expected to propose an efficient way to estimate relevant parameters. As there are a lot of points in the state space, we try to evaluate the value function only at a finite grid of points randomly drawn over state space. First, let's denote K_t as a subset of I_t . At the last period T,

1. Calculate $EV_T(I_T)$ for all $I_T \in K$:

$$EV_T(I_T) = \int\int \left\{ \max_{l,x} x_{lT} EU_{lT}(I_T) + \eta N_T + A_l + e_{lT} \right\} dG(e)dF(A) = \int \log\left(\sum_{l,x} \exp\left(x_{lT} EU_{lT}(I_T) + \eta N_T + A_l \right) \right) dF(A)$$

where ηN_T is neighborhood effects term, A_l is unobservable heterogeneity term, and x_T is the quantity choice variable. The potential problem is how to assume the probability distribution over A . Various trials will be implemented in this stage.

2. Run the following regression:

$$EV_T(I_T) = G(I_T)\theta^T + \varepsilon$$

where $G(I_T)$ is vector containing flexible transformation of the state variables: the mean profitability of each technology l, Y_l and the perception error variance σ^2_{Yilt}. Fortunately, A is assumed not to belong to the state space, so it's eliminated from $G(I_T)$.[38]
At T-1 period,
1. Draw M random variables:

$$\{v_1^m, \ldots v_L^m\}$$

from $v \sim N(o, \sigma_v^2)$ in (13).
2. For each state $I_{T-1} \in K$, compute the expected value of choosing technology l in $T-1$:

$$E\left[V_T(I_T) \mid I_{T-1}, d_{lT-1} = 1\right] = \frac{1}{M}\sum_m EV_T(I_T^m)$$

where I_T^m is the state corresponding to the m th draw and $d_{lT-1} = 1$.

If $I_T^m \in K$ use the exact solution,

Otherwise use $G(I_T^m)\theta^T$

3. For each $I_{T-1} \in K$ calculate $V(I_{T-1})$:

$$EV_{T-1}(I_{T-1}) = \int \log\left(\sum_{l,x} \exp\left\{x_{lT-1} EU_{lT-1}((I_{T-1})) + A_l + \beta E\left[V_T(I_T) \mid I_{T-1}, d_{jT-1} = 1\right]\right\}\right) dF(A)$$

The same problem in stage T occurs, it's necessary to find appropriate probability distribution over A.
4. Run the following regression:

$$EV_{T-1}(I_{T-1}) = G(I_{T-1})\theta^{T-1} + \varepsilon$$

Repeat step 1-4 for the remaining periods $t = T-2, \ldots, 0$
To get estimates, the model needs to be solved using the Interpolation/Simulation algorithm for each parameter values.

4.2. The Likelihood Function

The choice probabilities are computed by simulating a sequence of states for each farmer. As a sketch, this subsection follows Chintagunta et al. (2001).
Let's recall Equation (22),

$$\Pr(\{d_{ilt} = 1, x_{ilt}\} \mid I_{it}, \{d_{-ilt} = 1, x_{-ilt}\}) =$$

$$\int_\varepsilon \int_A \frac{\left(\exp\left(\begin{array}{l} x_{ilt} \cdot R\left[U_{ilt} \mid I_{it}\right] + x_{ilt} \cdot A_{il} + \eta N_{ilt} \\ + \delta E\left[\begin{array}{l} V_{it+1}(I_{it+1}, \{d_{-it+1}, x_{-it+1}\}) \\ \mid I_{it}, \{d_{ilt} = 1, x_{ilt}\}, \{d_{-ilt} = 1, x_{-ilt}\} \end{array}\right] \end{array}\right)\right)}{\left(\sum_{k=0,\ldots,L;\, x_{ikt} \in \mathbf{X}_{ik}} \exp\left(\begin{array}{l} x_{ikt} \cdot R\left[U_{ikt} \mid I_{it}\right] + x_{ikt} \cdot A_{ik} + \eta N_{ikt} \\ + \delta E\left[\begin{array}{l} V_{it+1}(I_{it+1}, \{d_{-it+1}, x_{-it+1}\}) \\ \mid I_{it}, \{d_{ikt} = 1, x_{-ikt}\}, \{d_{-ikt} = 1, x_{-ikt}\} \end{array}\right] \end{array}\right)\right)} F(A) g(\varepsilon) dA\, d\varepsilon \qquad (22)$$

Fortunately, our research is based on $T = 3$ period between 2005 and 2007. Chintagunta et al deals with the 3 observable periods problem. Let's denote that the component in the brace of exponential function

[38] It's not clear, commences are needed.

as $\tilde{V}_{idt} + A_{il}$, which is the sum of modified alternative specific value function and the unobservable term. $d \equiv (l, x)$ denotes the combination of technology-quantity choice. A_{il} is a time-invariant unobservable heterogeneity with a given conditional probability $F(A \mid I_i)$. Chintagunta et al. suggest a general likelihood function for the probability choice based on the binary case with serially independence as follows

$$\sum_{i=1}^{n} \ln \int \prod_{t=1}^{T} \begin{bmatrix} [p_0(I_i, A)]^{d_{i0}} [1 - p_0(I_i, A)]^{(1-d_{i0})} \cdot \\ \left[\frac{\exp(\tilde{V}_{ilt} + A_{il})}{1 + \exp(\tilde{V}_{ilt} + A_{il})} \right]^{d_{it}} \left[1 - \frac{\exp(\tilde{V}_{ilt} + A_{il})}{1 + \exp(\tilde{V}_{ilt} + A_{il})} \right]^{(1-d_{it})} \end{bmatrix} dF(A \mid I_i)$$

where $p_0(I_i, A)$ is the initial observations conditional on the information set and individual value function. It's a generalized expression of the likelihood over 2 continuous periods. For simplicity, we consider only technology adoption choices because the combination of the adoption and quantity choice makes computation messy. Then, Introducing multinomial choices and serial correlation, the above likelihood function is rewritten as

$$\sum_{i=1}^{n} \ln \int \prod_{t=1}^{T} \begin{bmatrix} \int [p_0(I_i, A)]^{d_{i0}} dG(e) \int [1 - p_0(I_i, A)]^{(1-d_{i0})} dG(e) \cdot \\ \int \left[\frac{\exp(\tilde{V}_{ilt} + A_{il})}{\sum_{k \in L+1} \exp(V_{ikt} + A_{ik})} \right]^{d_{it}} dG(e) \int \left[1 - \frac{\exp(\tilde{V}_{ilt} + A_{il})}{\sum_{k \in L+1} \exp(V_{ikt} + A_{ik})} \right]^{(1-d_{it})} dG(e) \end{bmatrix} dF(A \mid I_i)$$

Estimation strategy is based on finding parameters maximizing the above likelihood function.[39] Though we suppress quantity choices, it still looks complicated. In addition, the integral parts require appropriate arbitral distributions. Finally, initial condition problems must be considered. Considering initial periods, we can assign arbitrary values by taking expectations data between 2000 and 2004. Though they are not balanced panel data, it's necessary for getting initial values.

5. Discussion

5.1. Preliminary Results

If all the parameters are identified and estimated properly, the expected discussions are as follows: First, as for parameters for the utility, the price weights w_p and the risk parameter r are expected to be negative. This will be consistent with the conventional economic interpretation. In other words, farmers' utility (payoff) from adopting any GM technology will be decreased as bio-seed companies increase the seed price. Also, as it's mentioned previously, from the viewpoint that biotech-seed industry is highly concentrated, price coefficient will explain farmers' response to a few oligopolistic companies' market power. The negative r will show the typical propensity that farmers may exhibit aversion to utility risk if there is uncertainty from any adoption of technology. Similarly, farmers' profitability weight w_Y is expected to be positive.

The discussion of neighborhood effects η is described in 3.1.2. Briefly, the positive η would capture farmers' strategic behaviors - a tendency to act conversely against his neighbors do. Because it's modeled as a square term, a farmer's utility gain will increase as the deviation from mean level of peer group increases. For example, as he doesn't plant a specific GM trait corn adopted by other neighbors, he gets higher utility gains according to positive η. Then, his strategic behavior is to wait until observe

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[39] It may be wrongly derived.

what's going on during the planting year. On the other hand, the negative η is an expected utility (profit) loss. Then, farmers tend to follow others' choices. Otherwise, he comes to suffer from much profit loss. As a result, the case of η < 0 shows an evidence of neighborhood effects that agents follow his peers. If this is investigated over each GM trait, the differences will provide interesting stories acrossr GM technologies.

Other structural parameters associated with learning process will be major parts of this paper. Under the dynamic structural estimation, the identified mean profitability levels of each GM trait, Y_l for l = 0, …, 5, will show how different farmers' subjective beliefs are across technology. More interestingly, through the Bayesian updating procedure, the variance of the mean profitability level per each time period for each technology, $\sigma^2_{Y_{ilt}}$ will provide how they vary over time; if it decreases as time goes on, it's believed that there are learning effects as. The derived Kalman gain coefficients β_{ilt} are also suggesting how farmers' per period- and technology- weights vary in updating information. Lastly, for each GM trait, predicted diffusion path under simulated values concerning the mean profitability can be compared with observed diffusion path from data. It's meaningful whether the sigmoid curve of GM technology adoption is explained by learning process. Then, the comparison between two paths can account for the roles of externalities, which is described further in the following subsection.

5.2. Evaluation of Externalities

In analyzing determinants affecting farmers' biotechnology adoption behaviors, the roles of externalities have been emphasized through this paper. This study pays attention to learning process and neighborhood effects in terms of social interaction in communities. The way of evaluating their impacts is to compare results from various arbitrary models. For example, from the initial settings in Equation (6), different types of models can be proposed by constraining specific parameters (Table 5). In addition, adoption levels such as choice probabilities or adoption ratio in acre shares can be predicted according to each model.

Table 5. Evaluation of Externalities

	$\delta \neq 0$	$\delta = 0$
$\eta \neq 0$	(I) Forward-looking model with neighborhood effects	(II) Myopia model with neighborhood effects
$\eta = 0$	(iii) Forward-looking model without neighborhood effects	(iv) Myopia model without neighborhood effects : model without any externalities

With 4 cases in Table 5, observed adoption levels from data can be compared one after another. Also, belief paths may be differently derived according to each model structure. If they show outstanding differences, it'll address the impact of any externality.

Also, the suggested different models are used in scenario simulations. Note that one advantage of the structural model is that policy experiments are performed freely by its construction. Then, from estimated parameters, some meaningful simulations can be implemented. As mentioned in Section 3.1.3, simulations about price variation is illuminated because it can link price response to the market concentration in the biotech seed industry. The amount of discount price D_{ilt} (in Table3.) can be used for a kind of price promotion strategy of bio-seed companies.

6. Contribution

This study is expected to make the following contributions. First, though GM technology has been widely studied by economists, lack of accumulated data in short history has impeded empirical analysis with dynamic framework, and made most of associated works stay at the static level analysis; to the knowledge, few researches about GM technology have tried to introduce the DP. These restricted works cannot account for virtual farmers' forward looking adoption behaviors which should be dealt with under the DP. With a unique and abundant panel dataset, this paper will suggest a dynamic approach in GMO related works.

The focuses on the role of externalities represented as farmers' learning process and neighborhood effects are worth wile to be analyzed because they account for the impacts of social interactions on technology adoption process. Most adoption studies have paid attention to farm and product characteristics, whereas few studies tried to analyze externalities, if ever, they were not about GM technology studies but about primitive technologies such as irrigation, plows, or relatively older technologies like HYVs. By exploring externalities in GM technology, it's possible how different adoption behaviors for the innovative biotechnologies in the U.S. are from those for other conventional technologies in the developing countries.

Methodologically, this paper is meaningful in trying to use the mixed discrete-continuous (though, it's slightly modified) dynamic model while most of DP works have solved simple binary choice problems in adoption studies. Also, the consideration about unobservable heterogeneity has been often omitted in learning process models. This paper will try to suggest a model considering both unobservable heterogeneity and serial correlation at the same time. Finally, this paper can propose a few interesting policy issues in GM technologies, such as food safety, market concentration, or environmental policy by specifying structural estimation approach.

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