Dynamics of Biotechnology Adoption: an Application to U.S. Corn

By

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Dedication

To my wife, my parents-in-law, my mother

and

my father in heaven

Abstract

This research develops a dynamic analysis of the role of risk and learning in technology adoption, with an empirical focus on the adoption of Genetically Modified (GM) corn in the U.S. Corn Belt. A conceptual structural dynamic programming (DP) model is developed to capture the relative roles of individual and social learning under uncertain profitability for both conventional and GM technology.

The DP model involves solving Bellman equation under imperfect state information. It relies on *sufficient statistics* given by the mean and variance of profit under normality assumption. Farmers' learning process is given by the evolution of the mean and variance of profit and represented by the Kalman filter algorithm, where degrees of individual learning and social learning are parameterized. And farmers' risk aversion is specified using an additive mean-variance utility function under normality and Constant Absolute Risk Aversion (CARA). Parameters are estimated by nesting the DP problem (Bellman equation with the Kalman filter) within a minimum-distance estimator.

The model is applied to a unique panel dataset of U.S. corn farmers collected by dmrkynetic (DMR). Four models of farmers' adoption pattern are developed. First, an aggregate model of a representative farmer is applied, covering the whole DMR panel dataset (a benchmark case). Second, three disaggregate models are applied to three sub-groups of farmers: the early-, the intermediate-, and the late- adopters of GM technology. The disaggregate models allow the investigation of parameter heterogeneity across groups of farmers.

For each model, parameter estimates indicate that farmers are risk-averse, and that both individual learning and social learning affect the adoption of GM technology. The analysis shows that the effects of individual learning are greater than the effects of social learning.

Hypothesis testing is conducted on selected key parameters. Our results indicate that risk aversion, individual learning, and social learning have significant impacts on adoption decisions. Sensitivity analysis is also implemented to evaluate the effects of risk aversion and social learning. At a high level of risk aversion, risk aversion is found to have a negative effect on GM adoption rates for all models. However, at low levels of risk aversion, higher risk aversion can sometimes increase GM adoption, reflecting the presence of diversification in portfolio selection. Social learning is found to contribute to lower GM adoption rates, reflecting the presence of information externalities: farmers have incentives to delay adoption and wait to observe what their neighbors do. Welfare analysis shows that in the case of GM adoption risk aversion makes farmers worse off. And while social learning can have either positive or negative effects on farmers' welfare, the empirical results show that farmers' actual social learning is close to the social optimum, implying that farmers seem to internalize the information externalities efficiently. Finally, there is evidence of heterogeneity across farm types, as estimated parameters vary across the disaggregate models. The analysis shows that the early adopters are less risk averse and they tend to rely less on social learning. Alternatively, late adopters tend to be more risk averse and to rely more on social learning.

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Chapter 1 : Introduction

1.1.Background: the Advent of GM Technology

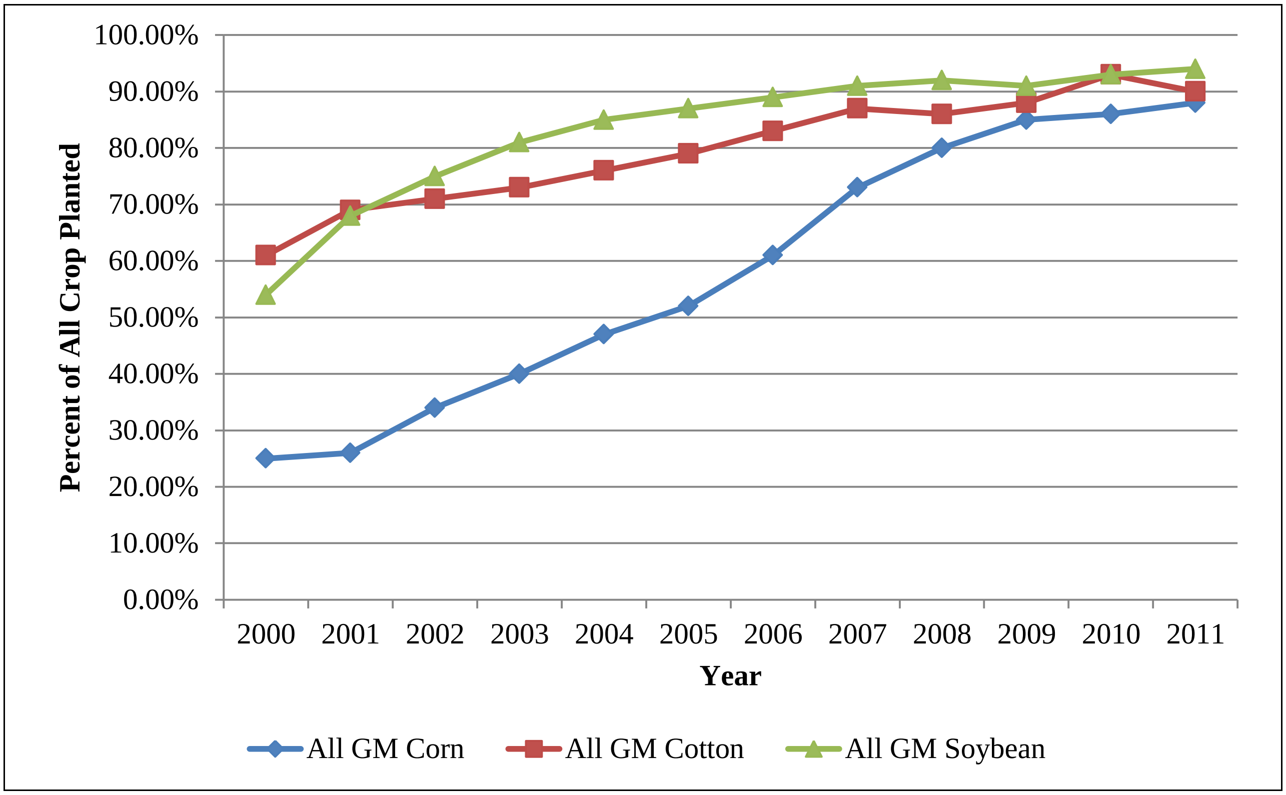
The diffusion of new technologies in the agricultural sector has been an important contributor to increases in farm productivity. For example, during the Green Revolution, high-yielding crops have had large positive effects on agricultural productivity and on the ability of the earth to feed a growing world population. The use of pesticide and herbicide also increased farm productivity. The introduction of modernized techniques (irrigation, tillage, and mechanization) has changed the paradigm of traditional agriculture, providing higher farm profit. That is, rapid technological progress has made important contributions to agriculture and to society (Feder et al., 1985; Griliches, 1995; Solow, 1994).

Since the mid 1990's, the advent of Genetically Modified (GM) seeds has provided farmers with new options to improve productivity and farm profit. Currently, the adoption rates of GM crops (corn, cotton, and soybean) amount to 91% on average in 2011 (USDA/NASS, 2011). As illustrated in Figure 1.1, the adoption rates of GM cotton have been increased from 61% in 2000 to 90% in 2011. The adoption rates of GM soybean have also increased from 54% in 2000 to 94% in 2011. The impact of GM corn has been even more dramatic: the adoption rates of GM corn went from 25% in 2000 but reaches 88% in 2011, showing the average growth rate of 252% while the average growth rates of GM cotton and GM soybean are 48% and 74% during the same period, respectively.

Such a rapid diffusion of GM crops is explained in part by their productivity effects. GM crops tend to have higher yield compared to conventional crops, along with improved weed and pest control, reductions in pesticide and herbicide usage, and reductions in operational costs of mechanic usage and energy associated with tillage or spraying pesticides and herbicides

(Brookes and Barfoot, 2011; Fernandez-Cornejo and Caswell, 2006). Both higher productivity and lower cost have provided farmers with higher profitability, and thus a strong incentive to adopt GM technology. However, not all farmers have adopted GM technology at the same time in spite of its technological advantages. This raises questions about the process of adoption and diffusion of a new technology: What are the factors that have played a role affecting GM technology adoption among farmers?

Figure 1.1: Adoption of GM Crops in the United States, 2000-2011



Source: USDA/NASS Acreage Survey (USDA, 2011).

1.2.Research Motivation

The adoption of GM technology comes with a question about which determinants have influenced farmers' adoption behaviors. This question has been raised and answered by economists in the field of agricultural technologies other than GM technology. Since Griliches

(1957) demonstrated that economic variables are major factors of adoption, observable farm characteristics have been analyzed in previous literature, such as farm size (Feder and O'Mara, 1981; Just et al., 1980), credit constraints (El-Osta and Morehart, 1999), location factors (Green et al., 1996; Thrikawala et al., 1999), education level or operator age (Barry et al., 1995; Batte and Johnson, 1993). The role of farmers' risk preferences has received special attention as most farmers are risk averse, and adopting a new technology typically contributes to increases in farmers' risk exposure (Feder and O'Mara, 1982; Feder et al., 1985; Hiebert, 1974; Mansfield, 1966).

Another branch of studies for technology adoption counts on information and externalities. First, adopters can learn about a new technology through their own experience, which is characterized as individual learning (Arrow, 1962; Lidner et al., 1979; Stoneman, 1981). But they can also learn from others (social learning), which constitutes a case of information externalities described in Belsey and Case (1993) (Bardhan and Udry, 1999; Besley and Case, 1994; Foster and Rosenzweig, 1995). However, the empirical analysis of individual learning and social learning is difficult due in large part to the lack of available empirical data, being less highlighted than empirical analyses of observable farm characteristics and risk preferences.

Though the adoption of a new agricultural technology has been highlighted from the various perspectives by researchers, GM technology adoption has received relatively less attention for several reasons. First, many studies of agricultural technology adoption have focused on case studies in developing countries in Africa (Batz et al., 1999; Conley and Udry, 2010), India (Besley and Case, 1994; Binswagner et al., 1980; Foster and Rosenzweig, 1995; Munshi, 2004), and Southeast Asia (Hiebert, 1974). But so far, GM technology has been less widely adopted in developing countries. It means the presence of a mismatch between observed GM adoption and data availability. Second, the history of GM technology is relatively short as it was first commercialized in 1996 in the U.S. Inadequate adoption observations in a short history prevent researchers from conducting empirical analyses on GM technology adoption, especially in case dynamic analyses are involved. Third, GM technology is rather different from other agricultural technologies: GM genes are typically patented by biotech-companies. Though most new innovations are patented, GM patents seem to limit farmers' choices more than most other input technologies. The large role played by private firms in the development and diffusion of GM technology has made it more difficult to acquire good farm-level data on GM adoption rates.

Few empirical studies both about the role of individual/social learning in agricultural technology adoption and about determinants affecting GM technology adoption motivate our empirical research. That is, there is a need for research examining the factors affecting GM technology adoption, especially in terms of the role of learning. As mentioned above, this need results from the situation that empirical analyses concerning the role of information externalities are rarely conducted due to lack of good data. In addition, any learning process inevitably involves dynamics, but understanding micro-level dynamics requires panel data collected over time for selected individuals. Unfortunately, such data are rather rare, which makes the empirical analysis of technology adoption and learning rather challenging. This argument applies to technology adoption in general, and to GM adoption by farmers in particular. Thus, our analysis focuses on GM technology adoption and the role of individual/social learning (information externalities) and risk preferences, with an application to GM corn in the U.S.

1.3.Research Object and Direction

This research examines the role of risk and learning in technology adoption, with an empirical focus on GM corn in the U.S. It includes studying the impacts of risk and risk aversion on GM technology adoption. Also, learning is evaluated as a process of improving farmers' assessment of a new technology and of allowing them to make better decisions. Though learning has been understood as playing an important role in technology diffusion (Feder and O'Mara, 1982; Hilbert, 1974), its empirical analyses have been challenging due to lack of good data as discussed above. The use of a unique extensive survey data collected by dmrkynetic (hereafter DMR)[1] enables us to conduct this empirical research as it addresses farm level information concerning adoption choices for both conventional and GM corn varieties.

The purpose of this research in this dissertation is to investigate learning process and risk preferences in an empirical model to explore how individual/social learning and risk preferences affect adoption decisions.[2] Farmers are assumed to learn about the profitability of conventional seed and GM seed from their own experiences and from observing neighboring famers' planting choices. Farmers' accumulated information affect whether and how much they adopt GM seeds for the next period. Such learning process takes place sequentially over time, and farmers make decisions with forward-looking behaviors. We specify the learning process using the dynamic programming (DP) model.

For this study, we develop a conceptual DP model of GM technology adoption capturing the joint role of individual and social learning. We apply the model to a unique panel data set of U.S. corn farmers (the DMR data). The DMR data includes farm-level adoption decisions for conventional and GM corn from 2000 through 2007 in the U.S. Corn Belt. We assume farmers'

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[1] http://www.gfk.com/gfk-kynetec/

[2] Some papers term individual learning as learning-by-doing, and social learning as learning from others (Bardhan and Udry, 1999; Foster and Rosenzweig, 1995). Throughout this paper, we use the term "individual learning" and "social learning."

reward function is represented by a mean-variance utility function. The analysis examines acreage decisions made at planting time, choosing between two technologies: conventional seed versus GM seed. At planting time, the profitability of each seed is not known, but its probability distribution can be assessed. Thus, this is a decision involving two risky choices of conventional seed and GM seed. Their state variables are characterized by the first and second moments of the distribution of the profitability for each technology. Learning is represented by the evolution of the assessed distribution of profit for each technology. The decision making is represented by a DP problem under imperfect state information as state variables (profitability for each technology) are unobservable. Learning is captured by observing variables that are correlated with farm profit for each technology. This includes both individual learning where each farmer observes their own past yields and social learning where each farmer observes his/her neighbors' behavior. To simplify the problem, we assume the unobservable state variables have a normal distribution. The normality assumption allows us to rely on a set of sufficient statistics - the first two moments of unobservable state variables. The evolution of mean and variance over time are given by the Kalman filter, which is a representation of learning.

Further, we nest the DP within a minimum-distance estimator and conduct hypothesis testing on the relative role of individual versus social learning. To do so, we devise a combined algorithm implementing a joint analysis of dynamic optimization and model estimation. Focusing on the role of risk preferences and the effects of social learning, we conduct sensitivity analysis of how the adoption of GM technology changes as those factors vary. In addition, welfare implications are also evaluated, capturing how farmers' welfare can vary with risk preferences and learning effects. In terms of social learning, we examine the impacts of information externalities, with a focus on both farmers' adoption behavior and farm welfare. For example, we document how information externalities inhibit technology adoption: farmers have an incentive to wait and delay their adoption decisions as they wait to obtain additional information from their adopting neighbors. Additionally, we study the presence of heterogeneity in adoption behavior across farmers. While our analysis starts with a representative farmer (his/her behavior representing aggregate behavior), we also examine adoption decisions made by different types of farmers. The results document the presence of heterogeneity across types of farmers, each type exhibiting different parameters. For example, we show that early adopters tend to be less risk averse and that they rely less on social learning in GM adoption decisions compared to late adopters.

This dissertation extends the analysis of GM technology adoption in several directions: First, we apply the structural approach instead of the reduced-form approach such as a logistic model previous adoption literature has used due to its relative ease (Fernandez-Cornejo et al., 2002). Second, we construct a conceptual structural model using the DP paradigm reflecting the underlying dynamic process essential in technology adoption (learning). Third, we incorporate learning processes into the adoption model using the Kalman filter algorithm, providing a convenient and flexible parameterized structure capturing relative roles of individual and social learning. Fourth, we analyze how individual/social learning and risk preferences affect adoption behavior by estimating corresponding parameters in the DP model with their econometric evidence through hypothesis testing. Fifth, we evaluate the sensitivity analysis and the welfare implications through simulations in terms of risk aversion and information externalities. Sixth, we model a continuous adoption choice problem rather than a discrete choice problem, providing a broader interpretation of the process of GM adoption on farms. Seventh, we devise an econometric process combining dynamic optimization nesting in model estimation. Finally, we analyze heterogeneity across farm types by conducting analysis both at the aggregate model and at disaggregate models.

The remainder of this dissertation is organized as follows. Chapter 2 reviews previous literature associated with GM technology adoption and the role of learning. Chapter 3 describes farmers' learning process for the profitability of GM corn. Also, it develops a conceptual dynamic model framework under imperfect state information, using the Kalman filter algorithm. Sufficient statistics are also introduced. Chapter 4 discusses the data used in the analysis and presents an algorithm implementing both dynamic optimization and model estimation. That is, the algorithm presents a solution method for the Bellman equation using the collocation method. And we propose an estimation strategy for the empirical DP model nested within a minimum distance estimator. Chapter 5 reports parameter estimation results for the aggregate model. Further, it presents hypothesis testing results, sensitivity analysis, and welfare analysis with a focus on the role of risk aversion and individual/social learning. Chapter 6 reports results for three types of disaggregate models reflecting the presence of heterogeneity across the early-, the intermediate-, and the late- adopters. Finally, Chapter 7 concludes the paper with a summary of the key findings and suggestions for future research.

Chapter 2 : Literature Review

This chapter reviews previous literature on the economics of technology adoption. Since the early work of Griliches (1957) on technology adoption, the literature has studied the many factors affecting technology adoption in agriculture. One of the main streams of research examines the impacts of farm characteristics, such as farm structure and size (Just et al., 1980), human capital (Barry et al., 1995; Batte and Johnson, 1993), credit constraints (El-Osta and Morehart, 1999), and location factors (Green et al., 1996; Thrikawala et al., 1999). The characteristics of technologies are also considered as determinants (Batz et al., 1999; Rogers, 1995). Another line of inquiry evaluates the role of risk preferences and their effects on farmers' technology adoption behavior (Feder et al., 1985; Feder and O'Mara, 1981; 1982; Hiebert, 1974; Mansfield, 1966). In addition to observable farm characteristics, the role of information in adoption behavior has also been examined (Arrow, 1962; Foster and Rosenzweig, 1995; Jovanovic and Nyarko, 1996), with special attention given to information and network externalities (Allen, 1982; An and Kiefer, 1995; Manski, 2000).

Many papers have investigated empirically the adoption of agricultural technologies in the context of developing countries. The adoption of GM technology has received less attention due in part to its short history and lack of empirical data. Previous literature on GM technology adoption examines the role of observable farm level characteristics (Fernandez-Cornezo and McBride, 2000) or risk preferences (Alexander et al., 2000; Liu, 2008; Qaim and Janvry, 2003), whereas information externalities or learning effects are seldom analyzed.

The first section reviews previous literature, both theoretical and empirical, on agricultural technology adoption with a focus on its determinants: farm characteristics, technology attributes, risk preferences, and externalities (neighborhood effects and learning effects). The following section reviews previous literature focusing on GM technology adoption. It helps situate this research and identify its contribution to the literature.

2.1.Determinants of Technology Adoption

In general, technology adoption in agriculture is influenced by farm characteristics, technology attributes, and externalities. Feder et al. (1985) summarize both theoretical and empirical literature on agricultural technology adoption, providing an extensive review of the observable farm characteristics affecting technology adoption. They classify farm characteristics as farm size, risk and uncertainty, human capital, labor availability, credit constraint, tenure, and supply constraints. Rogers (1995) and Batz et al. (1999) describe how the attributes of a new technology affect a farmer's adoption behavior. Besley and Case (1993) pay attention to externalities and their role in farmers' technology adoption decisions. They classify externalities into three categories: network externality, market power externality, and learning externality.

This section reviews previous literature concerning determinants of technology adoption under the following five categories: 1) observable farm characteristics described in Feder et al. (1985), 2) the attributes of agricultural technologies, 3) farmers' risk preferences and their effects on adoption, 4) neighborhood effects represented as network externalities as described in Besley and Case (1993), and 5) learning effects represented as information externalities in Besley and Case with distinction made between learning by doing and learning from others according to the origin of information (Foster and Rosenzweig, 1995).

2.1.1. Farm Characteristics

Early adoption literature focuses on the influences of farm level economic variables on technology adoption. Just et al. (1980) emphasize farm size, farm risk attitudes, and production technologies as determinants affecting the diffusion of new technologies. In terms of farm size, they show that a new technology is adopted earlier on larger farms than smaller farms, providing a critical lower bound on farm size where adoption becomes available given uncertainty and production cost. In addition, they show that the critical point of farm size increases with increments in production cost associated a new technology.

Farmers' ability to adopt technology depends on human capital, including operator age, education level, and years of farming experience. Generally, new technologies are expected to be adopted earlier by highly educated, more experienced, or younger farmers (Barry et al., 1995; Batte and Johnson, 1993). Fernandez-Cornejo et al. (1994) take operator labor and unpaid family labor into consideration as explanatory variables affecting the adoption of Integrated Pest Management (IPM), showing the probability of IPM adoption is higher as both the quantity and the quality of labor increase.

When a new technology requires a large initial investment, farmers' ability to use or borrow capital plays an important role in adopting that technology. In addition to typical farm characteristics described above, El-Osta and Morehart (1999) introduce credit constraints to analyze the adoption of both capital- and management- intensive dairy technology. Using USDA's 1993 Farm Costs and Returns Survey, they show that credit reserves positively affect the adoption of advanced milking parlors and a Dairy Herd Improvement (DHI) program.

Location factor can also be a crucial determinant of technology adoption. Across different locations, access to information and agro-ecological conditions (such as soil fertility, pest infestations, and weather conditions) are typically heterogeneous. Griliches (1957) finds that the diffusion of hybrid corn takes place at different rates across geographical regions due to the spatial heterogeneity of profitability. Green et al. (1996) emphasize the importance of agronomic characteristics in irrigation technology adoption. Thrikawala et al. (1999) show that the adoption of fertilizer management technology is affected more by the distribution of fertility than by the cost of fertilizer.

2.1.2. Technology Attributes

Farmers decide to adopt a new technology if it is profitable given farm-specific conditions (Feder et al., 1985; Rogers, 1995; Sunding and Zilberman, 2001). Then, the attributes of the new technology can affect its profitability directly. Rogers (1995) conceptualizes technology attributes from the viewpoints of relative advantage, compatibility, complexity, trialability, and observability. Relative advantage indicates benefits from technology adoption, including improved profitability, labor-time saving, and cost reduction. Compatibility is understood as similarity with previous technologies. Complexity means the degree of difficulty in experiencing and using the new technology. Trialability relates to how easy experimentation is, and observability corresponds to the degree to which the payoff from the new technology are visible.

Empirical analyses of technology attributes are relatively few compared to the analyses of farm characteristics. Technology attributes relates to the demand for product/technology characteristics, and the relationship between perceptions of different product/technology attributes and the corresponding demand (Ackerberg and Rysman, 2005; Berry, 1994; Nevo, 2001).

Batz et al. (1999) consider relative complexity, relative risk, and relative investment of technologies as attributes affecting adoption and diffusion of a new technology. They conduct an empirical analysis of 17 dairy technologies at the Meru district in Kenya. They survey extension workers to assess relative complexity, risk, and investment for each technology. Results show that relative complexity and risk dominate relative investment of technologies, the speed of adoption being slower as technologies are relatively more complex and relatively more risky.

Most recently, Useche et al. (2009) examine the effect of GM technology attributes, such as herbicide savings, insecticide savings, labor savings, and yield improvements, on the adoption of GM corn varieties with the focus on relative advantage or profitability. Using survey data from corn farmers in the U.S. upper Midwest, they estimate shadow prices for each attribute, analyzing how each attribute affects demand of GM corn varieties.

2.1.3. Risk Preferences

As described above, risk and risk preferences have received some attention by adoption researchers with the perception that innovative technologies may be more risky than traditional technologies (Feder et al., 1985). For example, farmers may perceive a new technology to be risky, being uncertain about the profitability. Potential adopters may view its use as experimental (Mansfield, 1966).

Early literature on farm risk relies on survey data obtained from interviews asking farmers how they perceive their risky environment. Binswanger et al. (1980) measure farmers' risk aversion by conducting experiments with a sample of farmers in India, evaluating risk aversion and showing that risk and risk aversion have a negative impact of the adoption of fertilizer. O'Mara (1980) estimates a sample of Mexican farmers' subjective yield distribution for high-yield seed varieties (HYVs), showing how farm risk affects the adoption of HYVs.

Roumasset (1976) argues that HYVs are not fully adopted by farmers in spite of their higher yield performance. He concludes that the consideration of risk leads farmers to diversify and allocate land to both HYV and traditional technologies, thus slowing down the adoption of HYV.

In addition to risk and risk preferences, the importance of learning or experience is often emphasized. Hiebert (1974) argues learning plays a key role in reducing uncertainty, providing empirical evidence that learning increases the likelihood of adopting high yielding varieties of rice in the Philippines. Feder and O'Mara (1981) show that risk aversion inhibits the adoption of HYVs in the presence of significant fixed costs in learning. The role of learning is discussed in more details in the Section 2.1.5.

2.1.4. Neighborhood Effects

At a given time period, a new and profitable technology could be considered as a public good to the extent that it is available to a large number of farmers (Dybvig and Spatt, 1983). In this context, farmers can obtain information about the new technology by observing their neighbors' adoption decisions. This is a case of network externalities described in Besley and Case (1993), also termed neighborhood effects or peer-group effects. Such neighborhood effects are externalities since a farmer's behavior is affected by his/her neighbors' behaviors in a cohort defined as a neighborhood group.

As neighborhood effects take place through social interaction with neighbors, they need to be identified separately from other forms of learning (Foster and Rosenzweig, 1995). Following Baerenklau (2005), neighborhood effects are defined as situations where a farmer's adoption choice is affected by contemporaneous neighbors' choices. This does not rule out the possibility that farmers obtain other information from their neighbors. Thus, neighborhood effects occur when a farmer adopts a new technology by viewing neighbors' adoption decisions themselves.

Neighborhood effects have not been studied extensively by economists. More research on this topic has conducted by social scientists in sociology, education, and geography (Durlauf, 2004; Jencks and Mayer, 1990). The applications of neighborhood effects in economic models are discussed by Manski (2000) and Brock and Durlauf (2001a, 2001b, 2002). Such models often suffer from an identification problem in econometric methodologies (Manski, 1993).

Allen (1982) examines adoption behaviors under network externalities from local neighborhoods, using statistical mechanics models. Kiefer (1995) evaluates the speed of technology adoption and its relationship with the number of neighboring adopters. Case (1992) analyzes a case study of sickle adoption in rural Indonesia, presenting an estimation method that is robust to the presence of neighborhood effects. Baerenklau (2005) incorporates neighborhood effects into a strategic dynamic model with risk preferences and learning. Using survey data from Wisconsin dairy farms, he analyzes the adoption of Management Intensive Rotational Grazing (MIRG) technology. He shows how to incorporate neighborhood effects in the estimation of factors affecting adoption decisions.

2.1.5. Learning Effects

Learning is the process of obtaining information, often in the context of making better decisions. This is relevant to technology adoption since little information may be initially available about a new technology. Bardhan and Udry (1999) categorize learning process as learning-by-doing and learning from others according to the source of information.

Learning-by-doing identifies an individual's own information acquisition in an isolated situation (Arrow, 1962; Lidner et al., 1979). Bayesian learning is often applied in investigating a typical sigmoid adoption and diffusion curve for a new technology (Stoneman, 1981). Then, the learning process is consistent with Bayes' theorem applied to subjective probabilities and the updating of prior belief into posterior beliefs as new information becomes available. In terms of agricultural technology, learning-by-doing occurs when farmers conduct their own experiments on their farm, such as testing new seeds, spraying new agrichemicals, or purchasing new combines.

Learning from others involves social interactions with other farmers. It can affect technology adoption jointly with farmers' learning-by-doing (Bardhan and Udry, 1999). As learning from others implies that other agents' behavior affect one's decision making, it introduces strategic behavior among agents. Strategic behavior reflects the presence of externalities across agents. Learning from others may affect adoption decisions. Indeed, if individuals decide to wait and see what their neighbors are doing before adopting a new technology, then learning from others would tend to slow down the adoption process. This kind of strategic delay corresponds to a free-rider problem (Kapur, 1995; McFadden and Train, 1996; Vives, 1997).

Both learning-by-doing and learning from others have been studied in the adoption literature. One line of inquiry is to apply the target-input model developed by Prescott (1972) and Jovanovic and Nyarko (1994). Foster and Rosenzweig (1995) analyze social learning relevant to adoption decision of HYV cotton in India by using survey data from the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT). They assume that a farmer's profit decreases with the square of the distance between his/her actual input level and the unknown optimal input level called as target, explaining information acquisition 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. They show that imperfect knowledge inhibits adoption of HYVs, and that both own experience and neighbors' experience increase HYV profitability. They assume that a new technology is always superior and known with certainty when a farmer makes his/her input decision.

While Foster and Rosenzweig (1995) assume that uncertainty arises only in a farmer's input management, Besley and Case (1994) propose that a new technology is risky and that its profitability is uncertain and exogenous. In contrast with Foster and Rosenzweig, as farmers are uncertain about whether a new technology is profitable or not, the technology is not always adopted. Using data from ICRISAT surveys in India, they focus on the impacts of the adopter's own experience and learning from others' behaviors on the adoption of HYV cotton varieties. Their results show that an individual farmer's adoption of HYV cotton is correlated with his/her neighbors' adoption decisions through social learning. Similarly to Besley and Case, Baerenklau (2005) assumes MIRG technology is risky and uncertain, incorporating both learning-by-doing and learning from others with risk preferences and neighborhood effects described in previous sections. He examines the potential of free-riding on neighbors' experience as farmers may wait and see what happens to neighbors in the presence of information or network externalities.

Using HYV wheat and rice data from the Indian Green Revolution, Munshi (2004) evaluates the intensity of social learning across technologies. HYV rice technology is more sensitive to unobserved farm characteristics with greater heterogeneity in growing condition than HYV wheat technology. Empirical results show that the effect of social learning is weaker in adopting HYV rice than in adopting HYV wheat. Conley and Udry (2010) pay attention to the role of spatial correlation in profitability shocks. Using data from pineapple farmers in the Akwapim South district of Ghana, they show farmers adopt the fertilizer technology following neighbors when neighbors face a favorable shock.

2.2.Literature on GM Technology Adoption

As described in the previous section, various agricultural technologies have been analyzed in previous literature. This section focuses on the case of GM technology adoption.

As most of adoption literature has focused on farm attributes following Griliches (1957), studies concerning GM technology adoption also have emphasized the significance of observable farm characteristics. Considering farm size and farmers' education level as crucial determinants, Fernandez-Cornezo et al. (2001) examine the adoption of HT soybeans, HT corn, and Bt-corn in the U.S. Using data from USDA's 1998 Agricultural Resource Management Study (ARMS), they show that the impact of farm size on adoption differs across technologies according to the adoption stage. For example, the adoption of HT soybeans is invariant by farm size, but the adoption of HT corn increases with farm size. This seems to reflect that HT corn technology is still at the innovator stage while HT soybeans technology has been around longer (Rogers, 1995). In addition, results show that higher education level lead to higher adoption rates of HT corn and Bt-corn.

Like other agricultural technology adoption literature, risk preferences are considered as key factors accounting for the adoption of GM technology. Using survey data from the Iowa Farm Bureau Federation, Alexander et al. (2003) analyze the impact of risk preferences on the adoption of GM corn and GM soybean by farmers in Iowa. They show that risk preferences influence the decision to plant GM corn but not GM soybeans. Qaim and Janvry (2003) analyze

Bt-cotton adoption in Argentina under a monopoly pricing regime. After gathering farmers' willingness to pay data, they find that farmers' average willingness to pay for Bt-cotton is less than the actual technology cost, reflecting that farmers are risk averse to GM technology. Recently, Liu (2008) conducted experiments to see how farmers' risk preferences affect adoption timing. Using survey data and field experiment data from Bt-cotton farmers in China, she shows that more risk-averse farmers adopt Bt-cotton later and that less risk-averse farmers are early adopters.

As discussed in Section 2.1.2, technology attributes affect GM technology adoption. Classifying corn varieties as non-GM corn, HT corn, Bt-corn, stacked (HT/Bt) corn, Useche et al. (2009) develop a trait-based adoption model incorporating technology attributes (traits), such as herbicide savings, insecticide savings, labor savings, and yield improvements, with other farm characteristics for each corn variety. Applying a mixed multinomial logit model, they measure the extent to which each trait impacts farmers' GM corn adoption decisions in the upper Midwest of the U.S. Their results show that technology attributes affect the adoption of GM corn varieties. For example, labor saving technologies have a wide potential for adoption.

2.3.Looking Ahead

Compared with previous literature on other agricultural technologies, literature on GM technology adoption remains incomplete. First, the empirical significance of learning needs to be refined. Second, with learning process, the underlying dynamics remains poorly understood. Referring to Section 2.1.5, investigating the role of learning in GM technology in agriculture could benefit from both theoretic and empirical studies. With the understanding that technology adoption is a decision problem under uncertainty, learning is understood as a process that reduces uncertainty (Hiebert, 1974). Previous literature has relied on Bayes theorem in empirical adoption models (Feder and O'Mara, 1982; Lindner et al., 1979; Stoneman, 1981). This paper characterizes the learning process using the Kalman filter algorithm (Kalman, 1960). The use of the Kalman filter algorithm facilitates the analysis of general and flexible learning processes. As discussed in Section 2.1.5, learning is classified as learning-by-doing (hereafter, individual learning) and learning from others (hereafter, social learning), depending on whether information is acquired by an individual or by interactions with others. This paper focuses on the relative roles of individual learning and social learning in the context of GM technology adoption. Thus, as discussed in more details in Chapter 3, the Kalman filter algorithm is used to evaluate the role of both individual learning and social learning.

With the sense that learning affects adoption behavior sequentially over time, empirical models incorporating learning process should be constructed using the dynamic programming (DP) model, where farmers are assumed to make decisions with forward-looking behavior. However, previous literature on GM technology has not developed adoption models using the DP, in part due to lack of accumulated data. Indeed, early GM technology adoption literature has been presented using static cross-sectional analyses, such as a Tobit model (Alexander et al., 2003; Fernandez-Cornezo et al., 2001) or a mixed multinomial logit model (Useche et al., 2009). Accumulated data up to the mid 2000's enable researchers to rely on time-series studies, such as the classic diffusion model developed by Griliches (1957). For example, Fernandez-Cornejo et al. (2002) evaluate determinants of the diffusion rates of GM corn, soybean, and cotton using a logistic model. But they do not analyze the role of learning. The current challenge is to combine cross-sectional and time-series models to study GM technology adoption with learning effects.

Developing a conceptual DP model for GM adoption can build on the work of Manski (1993), specifying social learning in a dynamic choice model accounting for decision makers' strategic behavior. Besley and Case (1994) and Baerenklau (2005) are also useful references for this paper as they develop a structural dynamic model incorporating strategic interdependence of farmers and their neighbors. But models in Manski and Besley and Case are discrete choice models about whether to adopt a new technology or not. This paper extends this approach to a continuous choice model examining adoption rates. In addition, previous GM adoption literature examining the role of risk preferences has depended upon survey data or field experimental data (Alexander et al., 2003; Liu, 2008; Qaim and Janvry, 2003). This paper will evaluate the role of risk aversion empirically by specifying and estimating a risk aversion parameter within a conceptual adoption model.

Chapter 3 : Conceptual Model of GM Technology Adoption

This chapter develops a conceptual structural dynamic programming (DP) model of the GM technology adoption including both individual learning and social learning. Model development begins with considering a general DP model providing a basic representation of the underlying dynamic process for GM technology adoption. It involves a problem of imperfect state information (Berteskas, 1976) due to the unobservable distribution of profitability for GM and non-GM technologies. The learning process is specified using the Kalman filter algorithm, capturing both individual learning and social learning. The model will be applied relying on the DMR panel data set of corn farmers in the U.S. Corn Belt.

In the general DP model, the analysis of technology adoption focuses on a given farmer in a specific region. The region involves a Crop Reporting District (CRD) defined by USDA as a zone facing similar agro-climatic conditions. Farmers in a given region constitute the relevant neighbor group. For each planting year t, farmer i makes an adoption decision of how many acres he/she would sow using the k-technology. In our case, technology corresponds to the choice of seed types: $k = \{CONV, GM\}$, where $CONV$ represents the old technology of conventional (non-GM) seed, and GM corresponds to the new technology of GM seed.[3] Farmer i's total acreage at year t is denoted by J_{it}, and acreage sown to the k-seed by J_{it}^{k}. Farmer i's neighbors' total acreage is denoted as G_{it}, and G_{it}^{k} is the acreage planted to the k-technology by farmer i's neighbors.

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[3] Traits of GM corn seed can be itemized as follows: herbicide-tolerant (HT), insect-resistant for the European corn borer (IR-ECB), and insect-resistant for rootworms (IR-RW) for a single GM trait seed; double-, triple-, and quadruple- stacked seed by combinations of HT, IR-ECB, and IR-RW. For simplicity, this paper considers a simple choice between non-GM (conventional) vs. GM. Analyses of multiple choices of various GM traits are good topics for further research.

The rest of this chapter is organized as follows. The first section provides the theoretical background for the analysis, with a focus on the profitability of conventional seed and GM seed and the economic rationale for the adoption of GM technology. Under uncertainty about profitability, a model of learning process is described, and the farm level utility is specified. The second section develops a general DP model of GM technology adoption under imperfect state information. It relies on sufficient statistics for empirical tractability. The third section specifies the general DP model and discusses its empirical application to the U.S. corn farmers' GM seed adoption. The learning process is represented using the Kalman filter. Model specification is implemented both at the aggregate model and at the disaggregate models according to three farm types: early, intermediate, and late adopters.

3.1.Theoretical Model

3.1.1. Profitability under Uncertainty

Farmers adopt GM technology when they experience higher profit from planting GM seeds than from sowing conventional seeds (Rogers, 1995). As stressed by Besley and Case (1994) and Baerenklau (2005), profit from a new technology is uncertain, and GM seed is understood as a risky choice with uncertain profitability. Thus, the DP involves decision making under uncertainty.

In many models of adoption decisions under uncertainty, the payoff from old technology/products is assumed to be certain. For example, Besley and Case (1994) assume that the return from the traditional cotton seeds is known with certainty through farmers' historical experience while they assume that the return from HYV cotton seed is uncertain. Erdem and Keane (1996) assume that consumers' utility from traditional brand choices involves no risk and no learning. In our analysis, we suppose that both conventional seeds and GM seeds generate uncertain payoff and that both are subject to learning. Thus, we consider the case where both the new technology and the old technology give uncertain payoff. This introduces a role of learning for both technologies in the adoption choice.

Adopting and planting the k-technology seeds at time t provide farmers with information concerning the actual per-acre gross income $\tilde{\pi}_{it}^{k}$. Under uncertainty, gross income is not known ahead of time to farmers. At planting time, each farmer i perceives $\tilde{\pi}_{it}^{k}$ as a random variable with a given subjective probability distribution. Thus, $\tilde{\pi}_{it}^{k}$ is considered as an unobservable latent variable.

The latent variable $\tilde{\pi}_{it}^{k}$ must be estimated by the *i*-th farmer based on the information available. Define seed cost as p_{it}^{k} for the k-technology. Following Goldberger (1972), Zellner (1970), and others, the perceived per-acre profitability π_{it}^{k} is represented as follows:

$$\pi_{it}^{k} = \hat{\pi}_{it}^{k}\left(\mathbf{q}_{it}, \tilde{e}_{it}^{k}; A\right) - p_{it}^{k} \qquad \text{for } k = \{CONV, GM\}, \quad (3.1)$$

where $\hat{\pi}_{it}^{k}(\cdot)$ is a function of the vector $\mathbf{q}_{it}$, a vector of random disturbances $\tilde{e}_{it}^{k}$, and a vector of associated parameters A. The vector $\mathbf{q}_{it}$ includes all observable factors affecting gross income $\tilde{\pi}_{it}^{k}$ (e.g., farm size and farm location). The random disturbance $\tilde{e}_{it}^{k}$ includes all unpredictable factors such as weather effects, pest damages, and weed conditions. Finally, $\tilde{e}_{it}^{k}$ also includes aspects of productivity of the *k*-th technology not known to the *i*-th farmer at time *t*.

The presence of imperfect knowledge about the profitability π_{it}^{k} implies a need to assess its distribution function and its evolution over time. This is done by introducing observable measurements related to π_{it}^{k}, as discussed below in Section 3.2.2 and Section 3.3.2.

3.1.2. Theoretic Basis of Learning Process

Learning means updating farmers' information. When applied to technology, learning involves accumulated experience over time. Information acquired by farmers in any year affects their adoption decisions for the following year. At the same time, information is revised and updated from one year to the next. This process takes place recursively.

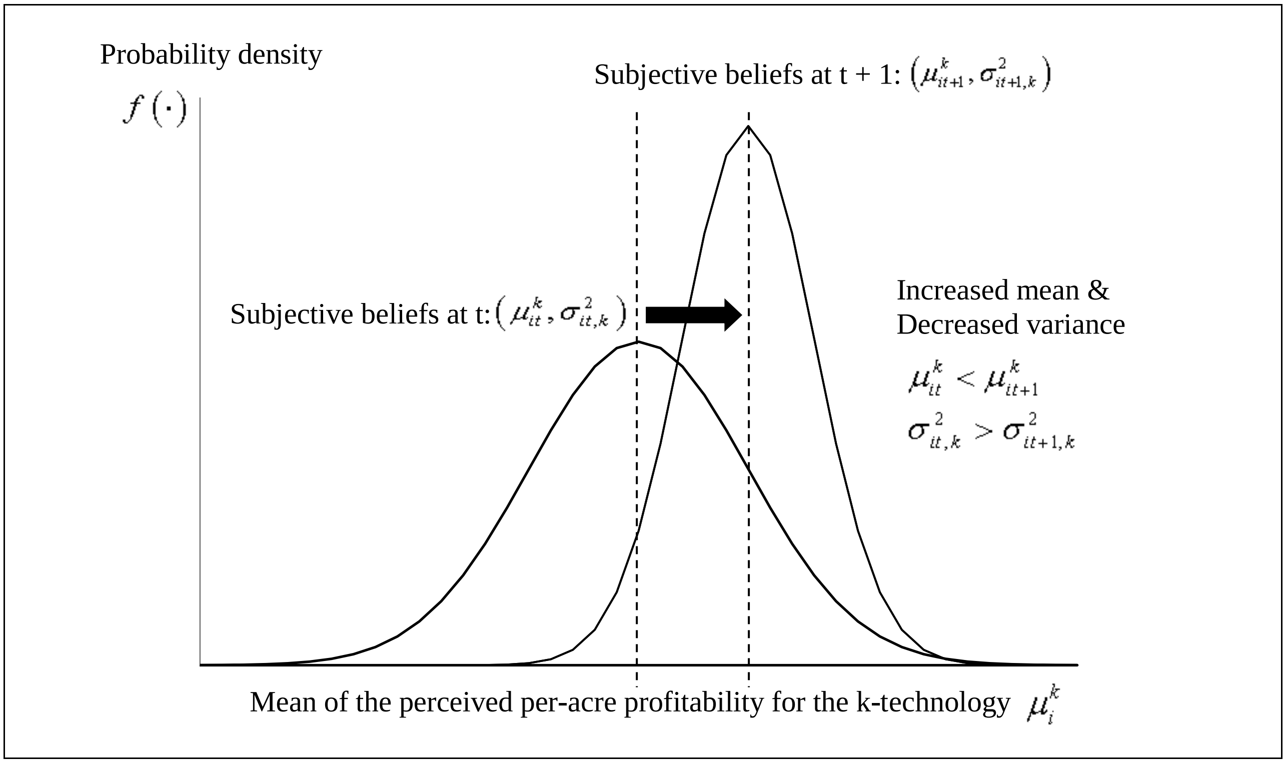
Noting that profitability π_{it}^{k} is not known ahead of time and thus uncertain (Baerenklau, 2005; Besley and Case, 1994), it can be treated as a random variable. Denote μ_{it}^{k} as the mean of the perceived per-acre profitability for the *k*-th technology at time *t*. Then, π_{it}^{k} can be written as

$$\pi_{it}^{k} = \mu_{it}^{k} + e_{it}^{k} \qquad \text{for } k = \{CONV, GM\}, \quad (3.2)$$

where the error term e_{it}^{k} is a random variable with zero mean and variance $\sigma_{it,k}^{2}$. Throughout this paper, information acquired from adopting the k-technology is represented by farmers' subjective beliefs given by the mean μ_{it}^{k} and variance $\sigma_{it,k}^{2}$ for the k-th technology at time *t*.

Figure 3.1 illustrates how the mean and variance of profitability can vary from one period to the next. The change reflects learning. For example, if farmer i experiences greater profit from sowing GM seeds than from planting conventional seeds at time t, he/she may expect the mean profitability level for GM seed μ_{it}^{GM} to increase in the next period. Further, he/she may expect a reduction in uncertainty on GM seeds in the next period (as represented by the variance $\sigma_{it,GM}^{2}$).

Figure 3.1: Subjective Beliefs at the Adoption Case



Most previous literature on learning has employed a Bayesian approach (Baerenklau, 2005; Besley and Case, 1994; Feder and O'Mara, 1982; Foster and Rosenzweig, 1995; Hiebert, 1974). Under the assumption that profit is normally distributed, they construct updating rules of μ_{it}^{k} and $\sigma_{it,k}^{2}$ using Bayes theorem. This is particularly convenient under normality as the normal distribution belongs to the class of conjugate distributions (DeGroot, 1970).

Below, we rely on the Kalman filter algorithm (Kalman, 1960) as a representation of learning. We do it for the following reasons. First, the Kalman filter algorithm provides a convenient parameterized structure for updating mean and variance as new information becomes available. Second, by assuming normality for the distribution of profitability, we can take advantage of its conjugacy property in the parameterized evolution of the mean and variance. Third, the Kalman filter is flexible and provides a basis to examine the relative roles of individual learning and social learning. More details on the analytical derivation of the Kalman filter under alternative learning processes are described in Section 3.3.1 and in the Appendix.

3.1.3. Risk Preferences: A Mean-Variance Approach

Under the expected utility model, assume that farmer i's risk preferences are represented by the von Neumann-Morgenstern utility function $u_{it}\left(\pi_{it}\right)$, where π_{it} denotes uncertain farm profit. Then the *i*-th farmer makes decisions that maximize expected utility $E\left[u_{it}\left(\pi_{it}\right)\right]$, where $E\left[\cdot\right]$ is the expectation operator over the distribution function of profit π_{it}.

GM technology takes time to diffuse fully because farmers are uncertain about its profitability. The latest adoption rate for GM corn amounts to 88% in 2011 (USDA/NASS, 2011). Yet, over the last 15 years, many farmers have sown both conventional seed and GM seed on their fields. This experimentation has provided new and useful information to farmers about the profitability of GM technology. As discussed above, we assume that both conventional seed and GM seed are risky choices giving uncertain payoff. When farmers face two risky technologies, they can choose mixture of both technologies in order to reduce risk exposure (variance), reflecting that farmers' technology adoption is a portfolio selection problem (Anderson et al., 1977). With farmers' diversification strategy under uncertain profitability, farmers' profit can be represented as a combination of partial adoptions over technologies. That is, farmer i's total profit π_{it} is obtained by taking summation over all acres and all technologies at time t as follows

$$\pi_{it} = \sum_{k\in\{CONV,GM\}} \left\{x_{it}^{k} \cdot \pi_{it}^{k}\right\}, \tag{3.3}$$

where $x_{it}^{k}=J_{it}^{k}/J_{it}$ indicates adoption rates of acres sown to the k-technology (J_{it}^{k}) relative to total acreage (J_{it}), and $x_{it}^{k}\in[0,1]$.[4]

Under the expected utility model, we assume that farmer i's risk preferences are given by a mean-variance utility function. Such an approach has been broadly used in applied risk analysis (e.g., Anderson et al., 1977). In the mean-variance approach, we have only to estimate the first two moments of the distribution of π_{it} to analyze farm utility from technology adoption under uncertain payoff (Chavas, 2004). Under normality, the mean and variance are sufficient statistics for the underlying distribution. In addition, we assume that farmer i's risk preferences exhibit Constant Absolute Risk Aversion (CARA) (Pratt, 1964). Under the assumptions of normality and CARA, maximizing farmer i's expected utility is equivalent to maximizing the additive mean-variance utility function represented as

$$\begin{aligned} E\left[u_{it}\left(\pi_{it}\right)\right] &= E\left[\pi_{it}\right]-\frac{1}{2}\cdot r\cdot \operatorname{var}\left[\pi_{it}\right] \\ &= \mathbf{x}_{it}^{\mathsf{T}}\cdot\boldsymbol{\mu}_{it}-\frac{1}{2}\cdot r\cdot\mathbf{x}_{it}^{\mathsf{T}}\cdot\Sigma_{it}\cdot\mathbf{x}_{it}, \end{aligned} \tag{3.4}$$

where r is the Arrow-Pratt absolute risk-aversion coefficient, measuring farmer i's degree of risk aversion.

The mean component $E\left[\pi_{it}\right]$ is specified using (3.3). For each technology k, we denote the mean of the perceived per-acre profitability π_{it}^{k} by μ_{it}^{k}.[5] Then, $\boldsymbol{\mu}_{it}=\left[\mu_{it}^{CONV}\quad \mu_{it}^{GM}\right]^{\mathsf{T}}$ denotes

[4] (3.3) is derived by $\pi_{it}=\sum_{k\in\{CONV,GM\}}\left\{J_{it}^{k}\cdot\pi_{it}^{k}\right\}=J_{it}\cdot\sum_{k\in\{CONV,GM\}}\left\{\left(J_{it}^{k}/J_{it}\right)\cdot\pi_{it}^{k}\right\}=J_{it}\cdot\sum_{k\in\{CONV,GM\}}\left\{x_{it}^{k}\cdot\pi_{it}^{k}\right\}$, where J_{it} is farmer i's total acreage at year t, and J_{it}^{k} is acreage sown to the k-seed. For simplicity, we assume constant returns to scale (CRS). Under CRS technology, farm size or scale doesn't matter. Thus, J_{it} is dropped from the derivation.

a vector of mean profitability. And $\mathbf{x}_{it} = \left[x_{it}^{CONV} \quad x_{it}^{GM} \right]^{\mathsf{T}}$ represents a vector of adoption rates for each technology. By taking the expectation operator $E[\cdot]$ to (3.3), we get

$$E[\pi_{it}] = \left[x_{it}^{CONV} \quad x_{it}^{GM} \right] \begin{bmatrix} \mu_{it}^{CONV} \\ \mu_{it}^{GM} \end{bmatrix} = \mathbf{x}_{it}^{\mathsf{T}} \cdot \boldsymbol{\mu}_{it} . \tag{3.5}$$

The variance component $\mathrm{var}[\pi_{it}]$ is also specified using (3.3). Σ_{it} is defined as the variance-covariance matrix of the per-acre profitability over technologies

$$\Sigma_{it} \equiv \begin{bmatrix} \sigma_{it,CONV}^2 & \mathrm{cov}\left(\pi_{it}^{CONV}, \pi_{it}^{GM}\right) \\ \mathrm{cov}\left(\pi_{it}^{GM}, \pi_{it}^{CONV}\right) & \sigma_{it,GM}^2 \end{bmatrix}, \tag{3.6}$$

where $\sigma_{it,k}^2 \equiv \mathrm{var}\left[\pi_{it}^k\right]$. By using the variance operator $\mathrm{var}[\cdot]$ along with (3.3) and (3.6), the variance of farmer i's profit, $\mathrm{var}[\pi_{it}]$ is represented as

$$\mathrm{var}[\pi_{it}] = \left[x_{it}^{CONV} \quad x_{it}^{GM} \right] \cdot \begin{bmatrix} \sigma_{it,CONV}^2 & \mathrm{cov}\left(\pi_{it}^{CONV}, \pi_{it}^{GM}\right) \\ \mathrm{cov}\left(\pi_{it}^{GM}, \pi_{it}^{CONV}\right) & \sigma_{it,GM}^2 \end{bmatrix} \cdot \begin{bmatrix} x_{it}^{CONV} \\ x_{it}^{GM} \end{bmatrix}$$

$$= \mathbf{x}_{it}^{\mathsf{T}} \cdot \Sigma_{it} \cdot \mathbf{x}_{it} . \tag{3.7}$$

The additive mean-variance utility function in (3.4) is used as a reward function in the DP model discussed in the following sections. Though the additive form holds only under restrictive assumptions of normality and CARA, this provides a convenient way to analyze farm utility under uncertain profit for the following reasons. First, CARA means the absence of wealth effects. In this context, a farmer's risk preferences are summarized by the absolute risk-aversion coefficient r (Chavas, 2004). Second, in the context of the DP, normality assumption enables us

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[5] Taking the expectation operator $E[\cdot]$ to (3.2), we obtain $E\left[\pi_{it}^k\right] = E\left[\mu_{it}^k\right] + E\left[e_{it}^k\right]$, where $\mu_{it}^k \equiv E\left[\pi_{it}^k\right]$ and $E\left[e_{it}^k\right]$ = 0.

to consider only the mean and variance of the distribution of π_{it}^{k} as sufficient statistics, which can reduce the high dimensionality of the imperfect state space in solving the Bellman equation, as discussed below in Section 3.2.3 (Berteskas, 1976).[6]

3.2.Conceptual Dynamic Model: A General Form

3.2.1. Basic Problem

We begin with considering a basic DP model for farmers' GM technology adoption. Suppose farmer i makes adoption decisions of how many acres to plant with k-technology seeds at each time period t, denoted by adoption rates $\mathbf{x}_{it} = \left[x_{it}^{CONV} \quad x_{it}^{GM} \right]^{\mathsf{T}}$. In the context of dynamic optimization problem, adoption rates correspond to choice variables.

At time t, farmer i faces uncertainty about the profitability of using conventional seeds versus GM seeds. The uncertain profits are represented by the per-acre perceived profitability $\boldsymbol{\pi}_{it} = \left[\pi_{it}^{CONV} \quad \pi_{it}^{GM} \right]^{\mathsf{T}}$. Then, his/her adoption choices are affected by the π_{it}^{k}'s for each technology k at time t. Thereby, π_{it}^{k}'s correspond to state variables farmer i face at time t. We assume that π_{it}^{k} evolves over time and that there exists a transition equation between π_{it}^{k} and π_{it+1}^{k} for each technology k.[7] Choosing adoption rates x_{it}^{k} under uncertain profitability π_{it}^{k} for each technology k, farmer i receives payoffs represented as his/her expected utility $E\left[u_{it}\left(\pi_{it} \right) \right]$

[6] Meyer (1987) presents a general case for mean variance analysis, without imposing normality assumption or CARA. In this context, the learning process could still be represented by the Kalman filter and our analysis would apply without assuming normality for the distribution of the unobservable state variables. However, Meyer's arguments are presented in a static context without any learning. In a dynamic context, there would be a need to identify non-normal conjugate distributions whose sufficient statistics can be summarized by the mean and variance only. Investigating this issue appears to be a good topic for future study.

[7] This is an intuitive assumption to set up a basic sequence problem. The underlying dynamics is explained by farmers' learning process, which is discussed in the following sections.

at time t, where π_{it} is given by equation (3.3). Assuming that farmer i's behavior is forward-looking, he/she makes adoption decisions to maximize his/her present expected value of future utilities. Then, the basic optimization problem can be represented as

$$V_{it} = \max_{\{\mathbf{x}_{it}\}_{t=0}^{T}} E_{\mathbf{v}_{it}}\left[\sum_{t=0}^{T}\left\{\delta^t \cdot E\left[u_{it}\left(\pi_{it}\right)\right]\right\}\right]$$

$$= \max_{\{\mathbf{x}_{it}\}_{t=0}^{T}} E_{\mathbf{v}_{it}}\left[\sum_{t=0}^{T}\left\{\delta^t \cdot E\left[u_{it}\left(\mathbf{x}_{it}^{\mathsf{T}} \cdot \boldsymbol{\pi}_{it}\right)\right]\right\}\right], \tag{3.8}$$

$$\text{s. t. } \boldsymbol{\pi}_{it+1} = \mathbf{g}_{it}\left(\boldsymbol{\pi}_{it}, \mathbf{x}_{it}, \mathbf{v}_{it}\right) \qquad \text{(the system equation)}, \tag{3.9}$$

where δ indicates a discount factor, $\delta \in (0,1)$. In equation (3.9), $\mathbf{v}_{it} \equiv \begin{bmatrix} v_{it}^{CONV} & v_{it}^{GM} \end{bmatrix}^{\mathsf{T}}$ is a vector of random disturbances for each technology $k = \{CONV, GM\}$. Equations (3.8)-(3.9) constitute a stochastic DP model, with state equation (3.9) representing the evolution of state variables over time.

As this paper focuses on learning, the role of learning needs to be made explicit in (3.8)-(3.9). When the state variables are not observed at planting time, learning is characterized by the evolution of the assessed probability distribution of the state variables. In this case, we face a DP problem with *imperfect state information* (Berteskas, 1976). As further discussed below, our analysis will proceed assuming that farmers' subjective beliefs are characterized by the mean and variance of the profitability π_{it}^{k} for each technology k, learning being represented by the evolution of the mean and variance over time.

3.2.2. Bellman Equation under Imperfect State Information

In the presence of unobservable state variables π_{it}^{k}'s under uncertainty, the basic sequence problem in the previous section is transformed to the DP problem with imperfect state information (Berteskas, 1976).

In addition to the system equation, we introduce *a measurement equation* in the DP model. When the state variables are not observed at planting time, farmers get information from observable measurements related to the unobservable states and use them to learn. At time t, let z_{it} be a vector of observable measurements providing information about the unobservable state variables π_{it}^{k}'s. In general, farmer i's available information set at time t is defined as

$$I_{it} = \left\{ z_{t0}, z_{t1}, ..., z_{it-1}, z_{it} \right\}. \tag{3.10}$$

Given the information set I_{it} at time period t, introducing the measurement equation involved with the vector of observable measurements z_{it} into the basic sequence problem in (3.8)-(3.9), the DP problem with imperfect state information is formulated as

$$\begin{aligned} V_{it} &= \max_{\{\mathbf{x}_{it}\}_{t=0}^{T} \mathbf{v}_{it}} E\left[\sum_{t=0}^{T} \left\{ \delta^{t} \cdot E\left[u_{it}\left(\pi_{it}\right) | I_{it} \right] \right\} \right] \\ &= \max_{\{\mathbf{x}_{it}\}_{t=0}^{T} \mathbf{v}_{it}} E\left[\sum_{t=0}^{T} \left\{ \delta^{t} \cdot E\left[u_{it}\left(\mathbf{x}_{it}^{\mathsf{T}} \cdot \boldsymbol{\pi}_{it}\right) | I_{it} \right] \right\} \right], \end{aligned} \tag{3.11}$$

$$\text{s. t. } \boldsymbol{\pi}_{it+1} = \mathbf{g}_{it}\left(\boldsymbol{\pi}_{it}, \mathbf{x}_{it}, \mathbf{v}_{it}\right) \qquad \text{(the system equation)}, \tag{3.12}$$

$$z_{it} = \mathbf{h}_{it}\left(\boldsymbol{\pi}_{it}, \mathbf{w}_{it}\right) \qquad \text{(the measurement equation)}. \tag{3.13}$$

With w_{it} being a random variable, the measurement equation (3.13) provides a general representation of the stochastic relationship between the unobservable state variables π_{it}^{k}'s and the vector of observable measurements z_{it} at time t.

In addition to the measurement equation (3.13), note that the information set I_t has also been introduced in (3.11), reflecting that decisions made at time t are conditional on this state. Applying *the state augmentation device* (Berteskas, 1976, Chapter 2), the evolution of information over time can be written in general as

$$I_{it+1} = \left\{ I_{it}, z_{t+1} \right\}, \tag{3.14}$$

which follows directly from the definition of information set I_{it} in (3.10). Equation (3.14) states how the information set expands over time as new observations on z are obtained each time period. When correlated with the unobserved states, these new observations are used to update the assessed probability distribution of the unobserved states. Then, the above DP problem becomes

$$V_{it}\left(I_{it}\right) = \max_{\mathbf{x}_{it}} \left\{ E\left[u_{it}\left(\pi_{it}\right) \mid I_{it} \right] + \delta \cdot \underset{z_{it+1}}{E}\left[V_{it+1}\left(I_{it+1}\right) \mid I_{it} \right] \right\}, \tag{3.15}$$

where farmer i's expected utility is now represented in terms of the conditional expectation operator given information set I_{it}, $E\left[\cdot \mid I_{it}\right]$. This indicates that farmer i's reward function involves the vector of observable measurements z_{it} via the information set I_{it}. In this context, dynamics of learning is represented by the evolution of the information set composed of observable measurements z_{it} farmer i receives every time period t. The remaining issue is to make the representation of the learning process empirically tractable in the DP problem.

As discussed in Section 3.1, we will assume that farmers' subjective beliefs for uncertain profitability π_{it}^k for each technology k are characterized by the first two moments of the distribution of π_{it}^k, the pair of the mean and variance (μ_{it}^k, $\sigma_{it,k}^2$). This mean-variance representation will prove very convenient: it means that the learning process can be characterized entirely by the evolution of mean and variance over time. This will greatly simplify our analysis on the role of learning in technology adoption. Given the information set I_{it}, we can infer the conditional mean and variance of π_{it}^{k} for each technology, and they can be specified through the conditional expected utility $E\left[u_{it}\left(\mathbf{x}_{it}^{\mathsf{T}} \cdot \boldsymbol{\pi}_{it}\right) | I_{it}\right]$. Learning about the distributions of π_{it}^{k} for each technology indicates that farmers update their beliefs (μ_{it}^{k}, $\sigma_{it,k}^{2}$) given I_{it}. Thereby, the evolution of I_{it} generates the updating of (μ_{it}^{k}, $\sigma_{it,k}^{2}$) implicitly. This updating is discussed in details in the following sections.

3.2.3. Bellman Equation with Sufficient Statistics

Solving the Bellman equation in (3.15) suffers from large computational burden as the information set I_{it} stores all measurements vectors z_{it}'s for every period. Such complexity of the information set can be reduced by employing *sufficient statistics*, which are quantities of smaller dimension than the original information set without loss of information necessary for solving the DP (Striebel, 1965). Sufficient statistics are defined as functions mapping the information set into the metric space such as the probability measures:

$$S_{it}^{k}\left(I_{it}\right) = P_{\pi_{it}^{k}|I_{it}}, \tag{3.16}$$

where $S_{it}^{k}\left(\cdot\right)$ indicates a sufficient statistic, and $P_{\pi_{it}^{k}|I_{it}}$ is its corresponding conditional probability measure associated with the imperfect state variable π_{it}^{k} for each technology k.

In a way similar to the discussion in (3.14), the system equation can be modified and simplified in Bellman equation by making use of sufficient statistics. Letting $\Phi_{it}^{k}\left(\cdot\right)$ as a function available from given data for each technology k, the new system equation is expressed as the evolution of the probability measure as follows:

$$P_{\pi_{it+1}^k | I_{it+1}} = \Phi_{it}^k \left(P_{\pi_{it}^k | I_{it}}, \mathbf{x}_{it}, z_{it+1} \right), \tag{3.17}$$

where the next period measurements vector z_{it+1} is considered as a random variable as it is in (3.14).

Note that equation (3.17) involves the evolution of the distribution of π_{it}^k instead of the values of π_{it}^k. This can be connected to farmers' learning process. Farmers learn about the distribution of π_{it}^k not the values of unobservable π_{it}^k. Also, learning process is represented as farmers' updating their subjective beliefs about the distribution of π_{it}^k. Thereby, equation (3.17) based on conditional probability measures reflects farmer i's learning process. Then, using sufficient statistics in (3.17), the Bellman equation becomes:

$$V_{it}\left(\mathbf{P}_{\boldsymbol{\pi}_{it}|I_{it}}\right) = \max_{\mathbf{x}_{it}} \left\{ E\left[u_{it}\left(\pi_{it}\right) | I_{it}\right] + \delta \cdot \underset{z_{it+1}}{E}\left[V_{it+1}\left(\boldsymbol{\Phi}_{it}\left(\mathbf{P}_{\boldsymbol{\pi}_{it}|I_{it}}, \mathbf{x}_{it}, z_{it+1} \right)\right) \middle| I_{it} \right] \right\}, \tag{3.18}$$

where $\mathbf{P}_{\boldsymbol{\pi}_{it}|I_{it}}$ is a vector of the conditional probability measures $P_{\pi_{it}^k|I_{it}}$, and $\boldsymbol{\Phi}_{it}\left(\mathbf{P}_{\boldsymbol{\pi}_{it}|I_{it}}, \mathbf{x}_{it}, z_{it+1}\right)$ denotes a vector of new system equations $\Phi_{it}^k(\cdot)$ for all k in (3.17).

The next step is to look for sufficient statistics in (3.17)-(3.18) that would reduce the dimension of the state space. This is important to help reduce the computational burden involved in solving the DP problem. Indeed, if $P_{\pi_{it}^k|I_{it}}$ has high dimensionality, solving Bellman equation would remain empirically difficult. In our case, assuming a Normal distribution helps. Then, $P_{\pi_{it}^k|I_{it}}$ can be characterized by only its mean and variance-covariance matrix, so that we can solve the relevant Bellman equation with relative ease over the smaller space of $P_{\pi_{it}^k|I_{it}}$ by relying on its first two moments (Berteskas, 1976).

By the assumption of normal distribution on $P_{\pi_{it}^k | I_{it}}$ for each technology k, the new system equation based on conditional probability measures in (3.17) accounts for updating rules in terms of farmers' technology adoption. Then, farmer i's subjective beliefs for each technology k are summarized by (μ_{it}^k, $\sigma_{it,k}^2$). Under normality, the first two moments (the conditional mean denoted by $\mu_{it|t}^k$ and the conditional variance denoted by $\sigma_{it|t,k}^2$)[8] are sufficient statistics for the conditional distributions of π_{it}^k given I_{it}, $P_{\pi_{it}^k | I_{it}}$.

Note that farmer i's expected utility is reformulated into the conditional expected utility given I_{it} as is in (3.15), involving the observable measurements to receive signals about unobservable state variables π_{it}^k for each technology k. Under normality and the additive mean-variance utility function in (3.4), we have

$$E\left[u_{it}\left(\pi_{it}\right) | I_{it}\right] = E\left[\pi_{it} | I_{it}\right] - \frac{1}{2} \cdot r \cdot \mathrm{var}\left[\pi_{it} | I_{it}\right]$$

$$= \mathbf{x}_{it}^{\mathsf{T}} \cdot \boldsymbol{\mu}_{it|t} - \frac{1}{2} \cdot r \cdot \mathbf{x}_{it}^{\mathsf{T}} \cdot \Sigma_{it|t} \cdot \mathbf{x}_{it} . \tag{3.19}$$

In (3.19), the conditional mean $E\left[\pi_{it} | I_{it}\right]$ and the conditional variance $\mathrm{var}\left[\pi_{it} | I_{it}\right]$ are used instead of the mean $E\left[\pi_{it}\right]$ and variance $\mathrm{var}\left[\pi_{it}\right]$ in (3.4) when the information set is I_{it} at time t. In the second equality in (3.19), corresponding components $\boldsymbol{\mu}_{it|t}$ and $\Sigma_{it|t}$ are also substituted

[8] The conditional moments given I_{it} are distinguished from the unconditional moments according to whether the information set I_{it} is considered or not at time t: for the distribution of unobservable π_{it}^k, if I_{it} is considered at time t, $\mu_{it|t}^k \equiv E\left[\pi_{it}^k | I_{it}\right]$ and $\sigma_{it|t,k}^2 \equiv \mathrm{var}\left[\pi_{it}^k | I_{it}\right]$. Otherwise, $\mu_{it}^k \equiv E\left[\pi_{it}^k\right]$ and $\sigma_{it,k}^2 \equiv \mathrm{var}\left[\pi_{it}^k\right]$ for each technology $k = \{CONV, GM\}$.

for $\boldsymbol{\mu}_{it}$ and Σ_{it}. The subscript $t\,|\,t$ indicates the conditional mean and variance are measured given information set I_{it} at time t.

Distinguishing from the unconditional moments described in Section 3.1.3, the conditional mean and variance of π_{it}^{k} given I_{it} for each technology k are denoted by

$$\boldsymbol{\mu}_{it|t} = \begin{bmatrix} \mu_{it|t}^{CONV} & \mu_{it|t}^{GM} \end{bmatrix}^{\mathsf{T}} , \tag{3.20}$$

$$\Sigma_{it|t} \equiv \begin{bmatrix} \sigma_{it|t,CONV}^{2} & \operatorname{cov}\left(\pi_{it}^{CONV}, \pi_{it}^{GM} \mid I_{it}\right) \\ \operatorname{cov}\left(\pi_{it}^{GM}, \pi_{it}^{CONV} \mid I_{it}\right) & \sigma_{it|t,GM}^{2} \end{bmatrix} , \tag{3.21}$$

where $\mu_{it|t}^{k} \equiv E\left[\pi_{it}^{k} \mid I_{it}\right]$ and $\sigma_{it|t,k}^{2} \equiv \operatorname{var}\left[\pi_{it}^{k} \mid I_{it}\right]$ for each technology $k = \{CONV, GM\}$. Then, farmer i's subjective beliefs given by (μ_{it}^{k}, $\sigma_{it,k}^{2}$) for the distribution of π_{it}^{k} can be analyzed through the conditional mean and variance of π_{it}^{k} given I_{it} ($\mu_{it|t}^{k}$, $\sigma_{it|t,k}^{2}$) for each technology k.

Using (3.19)-(3.21) along with the assumption of normal distribution on conditional probabilities $P_{\mu_{it}^{k}|I_{it}}$ for each technology k, Bellman equation in (3.18) becomes

$$V_{it}\left(\boldsymbol{\mu}_{it|t}, \Sigma_{it|t}\right) = \max_{\mathbf{x}_{it}} \left\{ \left(\mathbf{x}_{it}^{\mathsf{T}} \cdot \boldsymbol{\mu}_{it|t} - \frac{1}{2} \cdot r \cdot \mathbf{x}_{it}^{\mathsf{T}} \cdot \Sigma_{it|t} \cdot \mathbf{x}_{it} \right) + \delta \cdot \underset{z_{it+1}}{E} \left[V_{it+1}\left(\boldsymbol{\mu}_{it+1|t+1}, \Sigma_{it+1|t+1}\right) \middle| I_{it} \right] \right\} . \tag{3.22}$$

Note that we have only to consider two components of the mean $\boldsymbol{\mu}_{it|t}$ and the variance-covariance matrix $\Sigma_{it|t}$ as for evolving state variables in the context of sufficient statistics with the assumption of normal distribution. The transition equations between the current period pair ($\boldsymbol{\mu}_{it|t}$, $\Sigma_{it|t}$) and its consecutive pair ($\boldsymbol{\mu}_{it+1|t+1}$, $\Sigma_{it+1|t+1}$) can be obtained by applying the Kalman filter algorithm, as discussed in the following section and in the Appendix.

3.3. Model Specification: Empirical Application to the GM Technology Adoption in the U.S. Corn Belt

This section specifies the Bellman equation with sufficient statistics for our empirical analysis on GM corn adoption in the U.S. Corn Belt using the DMR panel dataset. Model specification requires combining dynamic optimization with econometric analysis of model estimation. Focusing on the effects of learning on GM technology adoption, the learning process is modeled using a measurement equation which is parameterized with coefficients capturing both individual and social learning. Noting that the process of information acquisition (learning) is represented by the updating of subjective beliefs about the distribution of the unobservable per-acre profitability for each technology, we rely on the Kalman filter algorithm to represent the evolution of the conditional mean and variance of the corresponding distribution over time.

A general form of the Bellman equation represented in (3.22) is specified at two models: at the aggregate model; and at a more disaggregate model, allowing for heterogeneity among farmers. The aggregate model is applied to the U.S. Corn Belt farmers from the whole DMR panel dataset, where we suppose there is a representative farmer whose GM corn adoption rates from 2000 to 2007 represent the average level of adoption during the same period. The disaggregate models applied to sub-groups drawn from the DMR panel dataset, classified by farm type in terms of adoption pattern. We divide farmers into three sub-groups depending on their adoption patterns: early adopters, intermediate adopters, and late adopters (Rogers, 1995).

For simplicity, within each group, we assume that farmers have the same policy function, i.e. that they would make the same decision when facing a given state. Note that this still allows differences in observed adoption to the extent that different farmers face different states. For example, even with the aggregate model, it remains possible to explain why some farmers are early adopters (late adopters) if they are in a state of being very well informed (poorly informed). In this case, heterogeneity of adoption across farmers would be due to differences in the initial conditions of the state space.

Thus, a single DP model is developed for each group both at the aggregate model (a representative farmer at average levels) and at the disaggregate models (a selected early-, intermediate-, and late- adopter). Solving a single DP problem for each analysis group helps us reduce the computational burden. Note that the disaggregate model being applied one group at a time, it will allow for heterogeneity across groups that are unrelated to initial conditions. This heterogeneity can come from differences in the reward function, in the system equation, and in the measurement equation across groups. This will provide a basis for us to investigate how risk preferences and social learning can affect adoption behavior across groups.

The DP model for the GM corn adoption is considered as an infinite time horizon problem though the DMR panel data is collected just for 8 years. The DMR panel dataset shows GM corn adoption rates increased dramatically from 33.01% in 2000 to 74.96% in 2007, but we can't say the adoption of GM seeds is at the steady state due to the possibility of increasing beyond the analysis period. For example, USDA/NASS (2011) shows the adoption rates of GM corn reach 88% in 2011. In addition, GM seeds don't always guarantee higher profit than conventional seed, reflecting that GM technology is not adopted fully. Thus, we assume farmers make adoption decisions of GM seeds under a long planning horizon and stationary conditions. Under an infinite horizon problem, this implies that the value function in Bellman equation doesn't depend on time t. Indeed, under the Contraction Mapping Theorem, Bellman equation is a functional fixed-point equation whose unknown is the common value function without time subscript.

3.3.1. Empirical Dynamic GM Adoption Model – Aggregate Model

***3.3.1.1.*System Equation and Measurement Equation**

The general DP model developed in Section 3.2 is empirically specified so that it is applied to the GM technology adoption by corn farmers in the U.S. Corn Belt. The relevant Bellman equation in (3.22) is specified for the aggregate GM technology adoption model, where a representative farmer is assumed to make adoption decisions at the average levels of economic variables in the DMR panel dataset.

As we solve a single representative farmer's adoption problem, farmer index i is omitted from the DP model hereafter. Specifying the aggregate DP adoption model begins with parameterizing the equations in the DP system with associated parameters. With a focus on relative roles of individual and social learning, learning process is modeled in the measurement equation with distinctive parameters capturing individual learning and social learning. The underlying dynamics representing learning process is modeled applying the Kalman filter algorithm. Assuming $\mathbf{g}_t$ in (3.12) and $\mathbf{h}_t$ in (3.13) are linear for simplicity, the system equation is represented as

$$\boldsymbol{\pi}_{t+1} = \boldsymbol{\alpha}\boldsymbol{\pi}_t + \boldsymbol{\beta}\mathbf{x}_t + \mathbf{v}_t \tag{3.23}$$

$$\Leftrightarrow \begin{bmatrix} \pi_{t+1}^{CONV} \\ \pi_{t+1}^{GM} \end{bmatrix} = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix} \begin{bmatrix} \pi_t^{CONV} \\ \pi_t^{GM} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \begin{bmatrix} x_t^{CONV} \\ x_t^{GM} \end{bmatrix} + \begin{bmatrix} v_t^{CONV} \\ v_t^{GM} \end{bmatrix}$$

for $k = \{CONV, GM\}$, where $\boldsymbol{\pi}_t$ is a vector of state variables π_t^{CONV} and π_t^{GM} representing the per-acre profitability of conventional seed and GM seed at time period t, respectively. $\mathbf{x}_t$ is a vector of adoption rates x_t^{CONV} for conventional seed and x_t^{GM} for GM seed. $\mathbf{v}_t$ is a random disturbance vector whose component v_t^k is assumed to be normally distributed with zero mean and a finite variance for each technology. $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are 2-by-2 matrices of parameters connecting the profitability and adoption choices at the current time period t with the values in the following period $t+1$.

In the system equation, the per-acre profitability for each technology is assumed to be stationary over time. Then, $\boldsymbol{\alpha}$ is assumed to be an identity matrix. β_{11} stands for the effect of adoption of conventional technology on the average change in the next period per-acre profitability of conventional seed π_{t+1}^{CONV}. If β_{11} > 0, adopting conventional seed would improve the profitability level of conventional seed at the next period. Symmetrically, β_{22} measures the effect of adoption of GM technology on the average change in the next period per-acre profitability of GM seed π_{t+1}^{GM}. If β_{22} > 0, the adoption of GM seed would improve the profitability for GM seed. Also, comparison between β_{11} and β_{22} can provide knowledge about which seed is more profitable. For example, if β_{11} < β_{22}, farmers may perceive GM seed is more profitable on average than conventional seed. The cross parameter β_{12} is the effect of adoption of GM technology on the average change in π_{t+1}^{CONV}, reflecting the effect of area-wide suppression of pest population. For example, if $\beta_{12} > 0$, the adoption of GM technology in this year would lead to higher π_{t+1}^{CONV} when planted GM corn seeds (e.g., IR-ECB or IR-RW corn varieties) suppress pest population not only on areas sown with GM seeds but also on their adjacent areas sown with conventional seeds (Hutchison et al., 2010). The other cross term β_{21} is the effect of adoption of conventional technology on the average change in π_{t+1}^{GM}. It can reflect the effect of weed control. For example, if $\beta_{21} < 0$, the weed control effect can be related to tillage and its impact on soil organic matter (Carter, 1992). On areas sown with conventional seeds at any year, tillage is necessary for weed control but tends to reduce organic matter during a cultivation period. If GM seeds are sown on the same areas in the following year, the profitability of GM seeds π_{t+1}^{GM} may be lower due to lower soil quality. On the contrary, sowing GM seeds, such as HT corn variety, instead of conventional seeds may slow down the decay of organic matter by reducing tillage and preserving soil quality.

Next, the measurement equation is represented as

$$z_t = \boldsymbol{\gamma}\boldsymbol{\pi}_t + \mathbf{w}_t \tag{3.24}$$

$$\Leftrightarrow \begin{bmatrix} q_{t-1}^{CONV} \\ y_{t-1}^{CONV} \\ q_{t-1}^{GM} \\ y_{t-1}^{GM} \end{bmatrix} = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \\ \gamma_{31} & \gamma_{32} \\ \gamma_{41} & \gamma_{42} \end{bmatrix} \begin{bmatrix} \pi_t^{CONV} \\ \pi_t^{GM} \end{bmatrix} + \begin{bmatrix} w_t^{q^{CONV}} \\ w_t^{y^{CONV}} \\ w_t^{q^{GM}} \\ w_t^{y^{GM}} \end{bmatrix}$$

for $k = \{CONV, GM\}$, where $z_t \equiv \left[q_{t-1}^{CONV}, y_{t-1}^{CONV}, q_{t-1}^{GM}, y_{t-1}^{GM} \right]^{\mathsf{T}}$ is the measurement vector composed of four elements capturing both individual learning and social learning jointly for each technology.

First, q_{t-1}^{CONV} and q_{t-1}^{GM} indicate yield information of conventional and GM seeds at the previous crop year $t-1$, respectively. We propose a farmer acquires information for the profitability referring to last year's yield data from his/her own experience at the adoption decision point t. In this case, q_{t-1}^{CONV} (q_{t-1}^{GM}) is used as a proxy variable capturing individual learning for conventional (GM) technology. Thereby, the previous year's yield information for each technology is an observable measurement involved with individual learning.

Second, y_{t-1}^{CONV} and y_{t-1}^{GM} indicate neighbors' adoption rates for conventional and GM technology at the previous year $t-1$, respectively.[9] At time period t, a farmer is assumed to observe what his/her neighbors did for the adoption of each technology in the previous year $t-1$. He/she obtains information about the profitability for each technology through social interactions, so that the previous year's neighbors' adoption rates for each technology are observable measurements involved with social learning.

Then, $\boldsymbol{\gamma}$ is a 4-by-2 matrix of corresponding parameters accounting for the relation between the per-acre profitability and observable measurements across technologies in the measurement equation. That is, $\boldsymbol{\gamma}$ reflects the degree of correlation between observation vector z_t and unobservable state variables π_t^{CONV} and π_t^{GM}. Specifically, γ_{11} (γ_{32}) indicates the effect of individual learning for conventional (GM) technology on the per-acre profitability π_t^{CONV} (π_t^{GM}). On the other hand, γ_{21} (γ_{42}) captures the effect of social learning for conventional (GM) technology on the per-acre profitability π_t^{CONV} (π_t^{GM}). In short, the relative roles of individual learning and social learning are measured by comparing γ_{11} and γ_{21} for conventional technology. A similar interpretation applies to the parameters γ_{32} and γ_{42} for GM technology. Especially, the social learning parameter for GM technology γ_{42} reflects the strength of information externalities, where farmers may have an incentive to delay adopting GM

[9] In the aggregate model, the neighborhood group is assumed to be the whole panel dataset for the U.S. Corn Belt, and y_{t-1}^{k} is given by taking average on $y_{it-1}^{k} = G_{it-1}^{k} / G_{it-1}$ for all farmers before we drop the subscript i, where G_{it-1}^{k} denotes acreage k -technology seed is planted to by farmer i 's neighbors at time period $t-1$ in the group. G_{it-1} is neighbors' total acreage at $t-1$ in the group.

technology as γ_{42} is greater. This is discussed in more detail through sensitivity analysis in Chapter 5.

Other parameters γ_{12}, γ_{22}, γ_{31}, and γ_{41} can be considered as cross-technology effects of individual learning and social learning. They can affect a farmer's diversification strategy in adopting multiple technologies. Especially, γ_{31} is associated with the effect of higher yield of GM on π_t^{CONV}; GM corn varieties can be considered as joint products of conventional and GM technologies as biotech companies insert specific GM traits into conventional seeds. For example, $\gamma_{31} > 0$ could occur when GM traits are inserted into better conventional seeds in order to improve yield of GM seeds.

$\mathbf{w}_t$ is a vector of observation noises for each component of z_t, being assumed to follow Normal distribution with zero mean and a finite variance. For simplicity, we assume that random disturbance vectors $\mathbf{v}_t$ and $\mathbf{w}_t$ are independent with given probability distributions. With the system equation (3.23) and the measurement equation (3.24), their distributions are assumed to be as follows:

$$E[\mathbf{v}_t] = 0, E[\mathbf{w}_t] = 0, M_t = E\left[\mathbf{v}_t \mathbf{v}_t^{\mathsf{T}}\right], N_t = E\left[\mathbf{w}_t \mathbf{w}_t^{\mathsf{T}}\right] \tag{3.25}$$

$$\Leftrightarrow \quad \begin{bmatrix} E\left[v_t^{CONV}\right] & E\left[v_t^{GM}\right] \end{bmatrix}^{\mathsf{T}} = \begin{bmatrix} 0 & 0 \end{bmatrix}^{\mathsf{T}},$$

$$\begin{bmatrix} E\left[w_t^{q^{CONV}}\right] & E\left[w_t^{y^{CONV}}\right] & E\left[w_t^{q^{GM}}\right] & E\left[w_t^{y^{GM}}\right] \end{bmatrix}^{\mathsf{T}} = \begin{bmatrix} 0 & 0 & 0 & 0 \end{bmatrix}^{\mathsf{T}},$$

$$M_t = \begin{bmatrix} \sigma^2_{v_t^{CONV}} & 0 \\ 0 & \sigma^2_{v_t^{GM}} \end{bmatrix}, \text{ and } N_t = \begin{bmatrix} \sigma^2_{q_t^{CONV}} & 0 & 0 & 0 \\ 0 & \sigma^2_{y_t^{CONV}} & 0 & 0 \\ 0 & 0 & \sigma^2_{q_t^{GM}} & 0 \\ 0 & 0 & 0 & \sigma^2_{y_t^{GM}} \end{bmatrix},$$

where M_t and N_t are 2-by-2 and 4-by-4 variance-covariance matrices for $\mathbf{v}_t$ and $\mathbf{w}_t$, respectively. We assume that M_t and N_t are positive definite matrices for every time period t.

*3.3.1.2.*The Kalman Filter Algorithm

As discussed in the previous sections, for each technology k, a farmer's beliefs for the per-acre perceived profitability π_t^k are characterized by the mean and the variance, μ_t^k and $\sigma_{t,k}^2$ along with Σ_t. Also, under the Normal distribution assumption, sufficient statistics for the adoption model are summarized by the conditional mean and variance of the probabilities associated with state variables, $\mu_{t|t}^k$ and $\sigma_{t|t,k}^2$ along with $\Sigma_{t|t}$. They are also used as state variables in Bellman equation with sufficient statistics in (3.22). Then, the learning process is constructed in a recursive way by means of the Klaman filter algorithm (Berteskas, 1976; Ljungqvist and Sargent, 2004).

Note that the conditional mean and variance given an observable measurement z_t [10], $\mu_{t|t}^k$ and $\sigma_{t|t,k}^2$ along with $\Sigma_{t|t}$ correspond to the linear least-squares estimation and its corresponding error covariance matrix of π_t^k in the context of the Kalman filter. Given the system equation (3.23) and the measurement equation (3.24), the evolution of $\boldsymbol{\mu}_{t|t} \equiv \begin{bmatrix} \mu_{t|t}^{CONV} & \mu_{t|t}^{GM} \end{bmatrix}^\top$ is derived as the following recursive formula[11]:

$$\boldsymbol{\mu}_{t+1|t+1} = \left[I - \Sigma_{t+1|t+1} \boldsymbol{\gamma}^\top N_{t+1}^{-1} \boldsymbol{\gamma} \right] \left[\boldsymbol{\mu}_{t|t} + \boldsymbol{\beta} \mathbf{x}_t \right] + \Sigma_{t+1|t+1} \boldsymbol{\gamma}^\top N_{t+1}^{-1} z_{t+1}, \qquad (3.26)$$

---

[10] Note that information set I_t is equivalent to the vector of observable measurements z_t in the specified DP model because I_t in Section 3.2 is reduced to a lower dimensional z_t using sufficient statistics.

[11] Further details are described in the Appendix.

where I is a 2-by-2 identity matrix. $\Sigma_{t+1|t+1}$ is the conditional variance-covariance matrix of π_{t+1}^{k} given z_{t+1}, whose dimension is 2-by-2. Accordingly, the evolution of $\Sigma_{t|t}$ is constructed as

$$\Sigma_{t+1|t+1} = \Sigma_{t|t} + M_t - \left[\Sigma_{t|t} + M_t\right]\boldsymbol{\gamma}^{\mathsf{T}}\left[\boldsymbol{\gamma}\left[\Sigma_{t|t} + M_t\right]\boldsymbol{\gamma}^{\mathsf{T}} + N_{t+1}\right]^{-1}\boldsymbol{\gamma}\left[\Sigma_{t|t} + M_t\right]. \qquad (3.27)$$

In addition to the evolutions of $\sigma_{t|t,CONV}^{2}$ and $\sigma_{t|t,GM}^{2}$, (3.27) provides the evolutions of covariance terms through the relation between $\Sigma_{t|t}$ and $\Sigma_{t+1|t+1}$. In order to focus on the evolutions of $\mu_{t|t}^{k}$ and $\sigma_{t|t}^{k}$, we assume that the covariance terms are decided by $\sigma_{t|t}^{k}$ for each technology k.[12] First, we assume that the covariance between π_t^{CONV} and π_t^{GM} is proportional to the correlation coefficient between yield of conventional seed and yield of GM seed, $\rho_{CONV,GM,t}$ at time t. Then, the covariance term is calculated from the estimated $\rho_{CONV,GM,t}$ with $\sigma_{t|t,CONV}^{2}$ and $\sigma_{t|t,GM}^{2}$ evaluated from the Kalman filter as follows[13]

$$\operatorname{cov}\left(\pi_t^{CONV}, \pi_t^{GM} \mid z_t\right) = \rho_{CONV,GM,t} \cdot \sqrt{\sigma_{t|t,CONV}^{2} \cdot \sigma_{t|t,GM}^{2}}\ . \qquad (3.28)$$

Then, given a constant $\rho_{CONV,GM,t}$, the covariance terms evolve automatically by evolutions in $\sigma_{t|t,CONV}^{2}$ and $\sigma_{t|t,GM}^{2}$ obtained from the Kalman filter rather than they evolve through Equations (3.26) and (3.27). Using these discussions, $\Sigma_{t|t}$ is represented as

$$\Sigma_{t|t} \equiv \begin{bmatrix} \sigma_{t|t,CONV}^{2} & \rho_{CONV,GM,t} \cdot \sqrt{\sigma_{t|t,CONV}^{2} \cdot \sigma_{t|t,GM}^{2}} \\ \rho_{GM,CONV,t} \cdot \sqrt{\sigma_{t|t,GM}^{2} \cdot \sigma_{t|t,CONV}^{2}} & \sigma_{t|t,GM}^{2} \end{bmatrix}. \qquad (3.29)$$

---

[12] The simplest way is to make the covariance terms zero, but it would ignore the existing correlation between conventional and GM technologies.

[13] Numerical details for $\rho_{CONV,GM,t}$ are discussed in Chapter 4

In sum, the evolutions of $\boldsymbol{\mu}_{t|t}$ in (3.26) and $\Sigma_{t|t}$ in (3.27) constitute the Kalman filter algorithm, representing a farmer's learning process concerning the distribution of the per-acre profitability π_t^k for the k-technology. Denoting S_t as the new state space under sufficient statistics, the state space associated with Bellman equation in (3.29) is summarized as $S_t = \left\{ \mu_{t|t}^{CONV}, \sigma_{t|t,CONV}^2, \mu_{t|t}^{GM}, \sigma_{t|t,GM}^2 \right\}$.

3.3.1.3. Bellman Equation for the Aggregate GM Technology Adoption Model

As assumed above, the DP adoption model is specified as an infinite time horizon problem. Then, the subscript indexing time t is omitted from the model, so that the value functions in the Bellman equation don't depend on time t any more. The next period terms indexed $t+1$ are simply denoted by subscript '$+$'. In the infinite horizon case, the value functions are same as $V_t(\cdot) = V(\cdot)$ for all t under stationarity. Then, the relevant Bellman equation in (3.22) is represented as the functional fixed-point equation whose unknown is the common time-invariant value function $V(\cdot)$.

Now, we consider combining econometric analysis of the DP adoption model (parameter estimation) with the given dynamic optimization problem. The system equation and the measurement equation (or equations in the Kalman filter) involve parameters to be estimated through the model simultaneously. All the parameters to be estimated are included in the parameter space denoted by $\Theta = \{r, \boldsymbol{\beta}, \boldsymbol{\gamma}\}$, where r is the Arrow-Pratt measure of absolute risk-aversion coefficient from the reward function, $\boldsymbol{\beta}$ is a 2-by-2 parameter matrix in the system equation, and $\boldsymbol{\gamma}$ is a 4-by-2 parameter matrix capturing individual and social learning in the measurement equation as discussed above. Now, our dynamic optimization problem is combined with a multivariate regression problem to estimate parameters in the system. Given the parameter space Θ and the state space denoted by S, the time-invariant value function is denoted as $V(S \mid \Theta)$ under stationarity. Combined with the parameter space Θ, Bellman equation under sufficient statistics in (3.22) is specified as

$$V(\boldsymbol{\mu}, \Sigma \mid \Theta) = \max_{\mathbf{x}} \left\{ \left(\mathbf{x}^{\mathsf{T}} \cdot \boldsymbol{\mu} - \frac{1}{2} \cdot r \cdot \mathbf{x}^{\mathsf{T}} \cdot \Sigma \cdot \mathbf{x} \right) + \delta \cdot \underset{z_+}{E} \left[V(\boldsymbol{\mu}_+, \Sigma_+) \middle| z \right] \middle| \Theta \right\}$$

$$\Leftrightarrow V(S \mid \Theta) = \max_{\begin{bmatrix} x^{CONV} \\ x^{GM} \end{bmatrix}} \left\{ \begin{array}{l} \left\{ \begin{array}{l} \begin{bmatrix} x^{CONV} & x^{GM} \end{bmatrix} \cdot \begin{bmatrix} \mu^{CONV} \\ \mu^{GM} \end{bmatrix} - \frac{1}{2} \cdot r \cdot \begin{bmatrix} x^{CONV} & x^{GM} \end{bmatrix} \\ \times \begin{bmatrix} \sigma^2_{CONV} & \rho_{CONV,GM} \cdot \sqrt{\sigma^2_{CONV} \cdot \sigma^2_{GM}} \\ \rho_{GM,CONV} \cdot \sqrt{\sigma^2_{GM} \cdot \sigma^2_{CONV}} & \sigma^2_{GM} \end{bmatrix} \\ \times \begin{bmatrix} x^{CONV} \\ x^{GM} \end{bmatrix} \end{array} \right\} \\ + \delta \cdot \underset{z_+}{E} \left[V(S_+) \mid z \right] \end{array} \middle| \Theta \right\}, \tag{3.30}$$

where S is the state space composed of the mean and the variance of the distribution of the k-th technology profitability π^k, $S \equiv (\boldsymbol{\mu}, \Sigma) = \left\{ \mu^{CONV}, \sigma^2_{CONV}, \mu^{GM}, \sigma^2_{GM} \right\}$. Then, the next period state space is represented as $S_+ \equiv (\boldsymbol{\mu}_+, \Sigma_+) = \left\{ \mu_+^{CONV}, \sigma^2_{+,CONV}, \mu_+^{GM}, \sigma^2_{+,GM} \right\}$, whose elements satisfy the following Kalman filter algorithm:

$$\begin{bmatrix} \mu_+^{CONV} \\ \mu_+^{GM} \end{bmatrix} = \left[I - \Sigma_+ \cdot \boldsymbol{\gamma}^{\mathsf{T}} N_+^{-1} \boldsymbol{\gamma} \right] \cdot \left[\begin{bmatrix} \mu^{CONV} \\ \mu^{GM} \end{bmatrix} + \boldsymbol{\beta} \cdot \begin{bmatrix} x^{CONV} \\ x^{GM} \end{bmatrix} \right] + \Sigma_+ \cdot \boldsymbol{\gamma}^{\mathsf{T}} N_+^{-1} z_+, \tag{3.31}$$

$$\Sigma_+ = \Sigma + M - [\Sigma + M] \boldsymbol{\gamma}^{\mathsf{T}} \left[\boldsymbol{\gamma} [\Sigma + M] \boldsymbol{\gamma}^{\mathsf{T}} + N_+ \right]^{-1} \boldsymbol{\gamma} [\Sigma + M], \tag{3.32}$$

where the variance-covariance matrix for the current period is

$$\Sigma = \begin{bmatrix} \sigma^2_{CONV} & \rho_{CONV,GM} \cdot \sqrt{\sigma^2_{CONV} \cdot \sigma^2_{GM}} \\ \rho_{GM,CONV} \cdot \sqrt{\sigma^2_{GM} \cdot \sigma^2_{CONV}} & \sigma^2_{GM} \end{bmatrix},$$

and the variance-covariance matrix for the next period is

$$\Sigma_{+} = \begin{bmatrix} \sigma^2_{+,CONV} & \rho_{CONV,GM,+} \cdot \sqrt{\sigma^2_{+,CONV} \cdot \sigma^2_{+,GM}} \\ \rho_{GM,CONV,+} \cdot \sqrt{\sigma^2_{+,GM} \cdot \sigma^2_{+,CONV}} & \sigma^2_{+,GM} \end{bmatrix}.$$

In addition, their corresponding random disturbances are

$$M = \begin{bmatrix} \sigma^2_{v^{CONV}} & 0 \\ 0 & \sigma^2_{v^{GM}} \end{bmatrix},$$

$$N = \begin{bmatrix} \sigma^2_{q^{CONV}} & 0 & 0 & 0 \\ 0 & \sigma^2_{y^{CONV}} & 0 & 0 \\ 0 & 0 & \sigma^2_{q^{GM}} & 0 \\ 0 & 0 & 0 & \sigma^2_{y^{GM}} \end{bmatrix}, \text{ and } N_{+} = \begin{bmatrix} \sigma^2_{q_+^{CONV}} & 0 & 0 & 0 \\ 0 & \sigma^2_{y_+^{CONV}} & 0 & 0 \\ 0 & 0 & \sigma^2_{q_+^{GM}} & 0 \\ 0 & 0 & 0 & \sigma^2_{y_+^{GM}} \end{bmatrix}.$$

As discussed in Section 3.2.2, $z_{+} = \begin{bmatrix} q^{CONV} & y^{CONV} & q^{GM} & y^{GM} \end{bmatrix}^{\mathsf{T}}$ plays a role of random disturbance as the yield information and neighbors' adoption rates are not observed by farmers at the same period. They can be observed in the following period.

Note that δ indicates a discount factor, $\delta \in (0,1)$ and that the reward function is represented by the additive mean-variance utility function, which is bounded for the k-th technology adoption choice $x^k \in [0,1]$. As long as δ is less than 1, and the reward function is bounded, the mapping in Bellman equation is a contraction on the space of bounded continuous function, being solved by the Contraction Mapping Theorem (Stokey et al., 1989). Then, a representative farmer's optimal adoption choices $\mathbf{x}^*(S \mid \Theta) = \begin{bmatrix} x^{CONV*}(S \mid \Theta) & x^{GM*}(S \mid \Theta) \end{bmatrix}^{\mathsf{T}}$ are also obtained by solving (3.30) given the parameter space Θ. Under stationarity of the infinite time horizon problem, the optimal policy function is also stationary. In the aggregate model, the parameter space Θ is assumed to be constant for all farmers. However, the initial condition of state space can reflect heterogeneity by changing initial values in any combination of elements in S, which can be implemented by simulations with different combinations in S.

The above dynamic optimization problem is expanded with the problem of estimation for the parameter space Θ. We count on a minimum-distance estimator (MDE) (Manski, 1988). The outline of algorithm is as follows: first, given any Θ, we solve the DP adoption model, obtaining optimal value functions and optimal policy functions given all possible state space. Second, we perform dynamic-path analysis (Miranda and Fackler, 2002). Using the optimal solutions, we simulate the adoption path over 8 years from 2000 to 2007. Third, we compare simulated adoption path with observed adoption path from the DMR panel dataset. We examine the discrepancies (distances) between observed adoption rates and simulated (predicted) adoption rates. Finally, using MDE, we estimate the parameter space Θ so as to minimize the distance. Further details are described in Chapter 4, where solution algorithm for dynamic optimization and estimation strategy are discussed.

3.3.2. Empirical Dynamic GM Adoption Model - Disaggregate Model

The aggregate model can provide a broad-brush understanding of the roles of risk preference and individual/social learning in GM technology adoption in a big picture. Considering an arbitrary representative farmer in the DMR panel dataset, it parameterizes the reward function, the system equation, and the measurement equation in the DP system to analyze how an average level farmer is affected in the adoption of GM technology by changes in key determinants such as risk preferences or individual/social learning. Technically, it reduces computational burdens by solving a single DP problem for a representative farmer rather than solving multiple DP problems for every farmer. Solution of a single DP is available by assuming that all farmers' policy functions are same and that heterogeneity exists only in initial conditions.

However, the aggregate model inevitably involves a potential aggregation bias problem by overlooking heterogeneity present at the more disaggregate model. First, the optimal policy function obtained from solving the aggregate adoption model is constant across farmers. Under the same policy function, simulated GM adoption rates can differ depending on the initial conditions facing each farmer. Indeed, even if the optimal policy function from the aggregate model holds for any individual farmer, different initial conditions (e.g., different initial quality of information) can imply different observed path of adoption across farmers. Yet, there remains the possibility that farmers can differ from each other for reasons unrelated to initial conditions. In this case, different farmers would have different decision rules which would in turn affect their observed adoption decisions. In this case, the aggregate model would suffer from heterogeneity bias. This issue is addressed in our analysis of DP models applied at the disaggregate models.

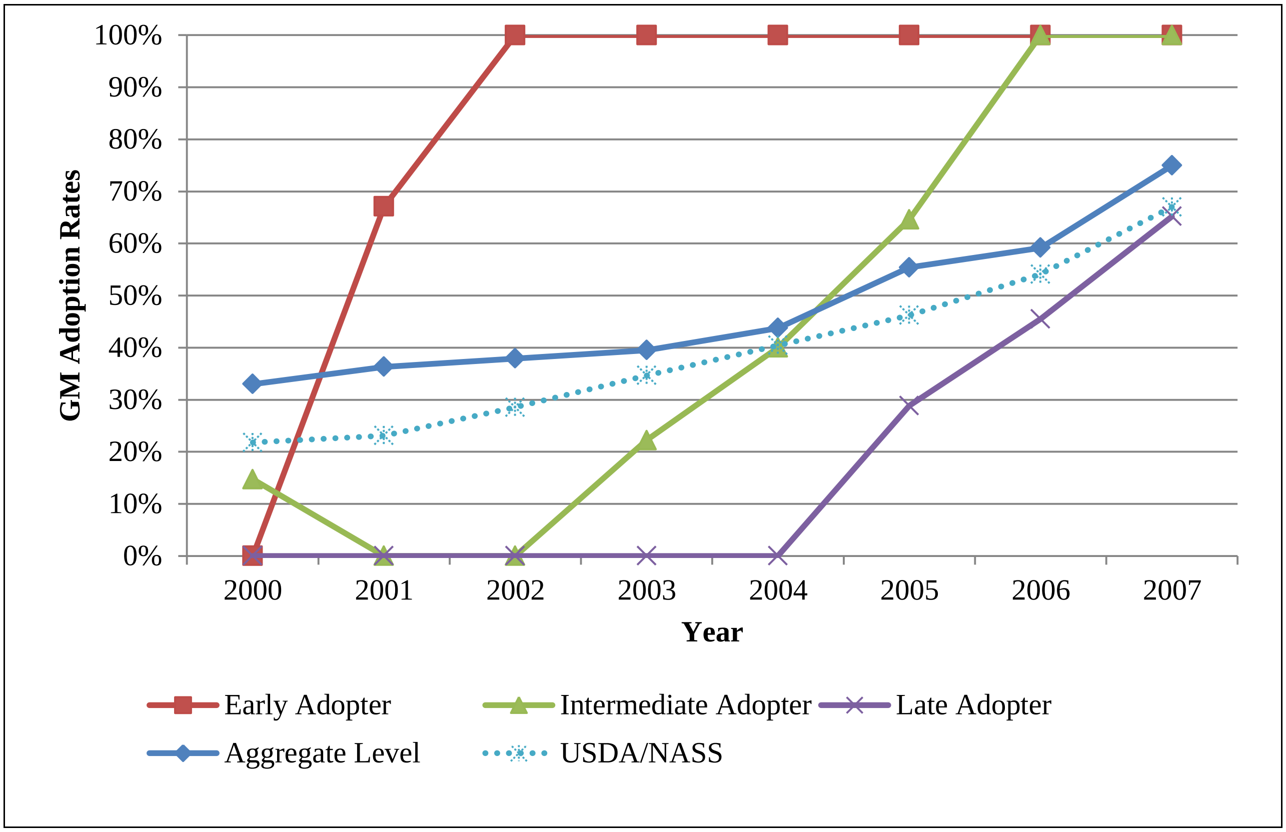
Second, our DP model implements both dynamic optimization solution and parameter estimation done jointly. As just mentioned, the presence of parameter heterogeneity across farmers can imply heterogeneity bias. If so, estimated parameters from the aggregate model may be biased and provide an inappropriate representation of an individual farmers' adoption behavior. This would occur if differences in the parameterization of the model affect the decision rules obtained from the DP problem.

Third, heterogeneity in reaction for externality (mainly, information externalities in terms of social learning) can occur across individual farmers. As our model captures information externalities through parameterization of the measurement equation, the strength of information externalities estimated at the aggregate model could be different across individual farms. This is similar to the above heterogeneity in the parameter space, but with a special focus on the role of social interactions and their effects on individual behavior.

Since ignoring heterogeneity across farmers can lead to biased results, we develop disaggregate DP models that can capture differences across groups. Investigating 136 farmers in the DMR panel dataset, we classify farmers into three types according to their adoption patterns. Referring to the typical s-shape adoption curve (Rogers, 1995), we identify early adopters as those whose GM corn adoption rates reach at a relatively high level in early 2000's (70% in 2002), late adopters as those whose adoption rates reach at a relatively high level between 2005 and 2007, and intermediate adopters as those situated between early adopters and late adopters. The motivation for this grouping is to explore whether there are significant differences in adoption behavior across groups, differences that are unrelated to initial conditions. We will focus our attention on the effects of two factors: the degree of risk aversion and the extent of social learning.

As in the aggregate model, the empirical DP models are solved once for each farm type. This assumes that farmers within each type use the same decision rules. But this greatly reduces computational burden of solving multiple DP models. As noted above, our analysis considers three farmer types: the early-, the intermediate-, and the late- adopter. Using the DMR data, Figure 3.2 illustrates observed adoption rates by each farmer type, the aggregate GM corn adoption rates from USDA/NASS are also drawn for comparison.

Figure 3.2: GM Corn Adoption Rates by the Selected Farm Type Farmers



Source: The DMR survey data and USDA/NASS (2011)
Note: Y-axis indicates adoption rates of planted acres to GM seed

In the analysis of farm heterogeneity, we want to explore whether the ability to access information about the profitability of GM technology differs across farm types. Intuitively, we expect early adopters to be better informed about the profitability of GM seed and late adopters to be less-well informed. While our three groups of farmers clearly exhibit different adoption patterns, we want to explore how much of the differences can be attributed to heterogeneity in initial conditions. Alternatively, we want to examine whether adoption behavior varies across farms types for reasons unrelated to initial conditions. In particular, we are interested in studying the role of social learning and answering the question of whether there is significant heterogeneity in information externalities across farm types. We also investigate whether there is heterogeneity in risk preferences across farm types. Addressing these issues requires solving a DP model for each type of farmer.

Let the set of farm types be $\{EARLY, INTER, LATE\}$, where a selected farmer's farm type is represented as $EARLY$ for an early adopter, $INTER$ for an intermediate adopter, and $LATE$ for a late adopter. Assumptions for the disaggregate adoption model are the same as those of the aggregate adoption model (normality, infinite time-horizon problem, and stationarity). The differences between the aggregate model and the l-type of disaggregate model involve initial conditions in the state space, observable measurements, and parameters to be estimated for each group. Given $l \in \{EARLY, INTER, LATE\}$ and using (3.23), the system equation for the l-type adopter is rewritten as

$$\boldsymbol{\pi}_{t+1}^{l} = \boldsymbol{\alpha}^{l} \boldsymbol{\pi}_{t}^{l} + \boldsymbol{\beta}^{l} \mathbf{x}_{t}^{l} + \mathbf{v}_{t}^{l} \tag{3.33}$$

$$\Leftrightarrow \begin{bmatrix} \pi_{t+1}^{CONV,l} \\ \pi_{t+1}^{GM,l} \end{bmatrix} = \begin{bmatrix} \alpha_{11}^{l} & \alpha_{12}^{l} \\ \alpha_{21}^{l} & \alpha_{22}^{l} \end{bmatrix} \begin{bmatrix} \pi_{t}^{CONV,l} \\ \pi_{t}^{GM,l} \end{bmatrix} + \begin{bmatrix} \beta_{11}^{l} & \beta_{12}^{l} \\ \beta_{21}^{l} & \beta_{22}^{l} \end{bmatrix} \begin{bmatrix} x_{t}^{CONV,l} \\ x_{t}^{GM,l} \end{bmatrix} + \begin{bmatrix} v_{t}^{CONV,l} \\ v_{t}^{GM,l} \end{bmatrix}.$$

And, the measurement equation for the l-type adopter is rewritten from (3.24) as follows:

$$z_{t}^{l} = \boldsymbol{\gamma}^{l} \pi_{t}^{l} + \mathbf{w}_{t}^{l} \tag{3.34}$$

$$\Leftrightarrow \begin{bmatrix} q_{t-1}^{CONV,l} \\ y_{t-1}^{CONV,l} \\ q_{t-1}^{GM,l} \\ y_{t-1}^{GM,l} \end{bmatrix} = \begin{bmatrix} \gamma_{11}^{l} & \gamma_{12}^{l} \\ \gamma_{21}^{l} & \gamma_{22}^{l} \\ \gamma_{31}^{l} & \gamma_{32}^{l} \\ \gamma_{41}^{l} & \gamma_{42}^{l} \end{bmatrix} \begin{bmatrix} \mu_{t}^{CONV,l} \\ \mu_{t}^{GM,l} \end{bmatrix} + \begin{bmatrix} w_{t}^{q^{CONV,l}} \\ w_{t}^{y^{CONV,l}} \\ w_{t}^{q^{GM,l}} \\ w_{t}^{y^{GM,l}} \end{bmatrix}.$$

Then, using (3.30), the disaggregate DP model for the l-type farmer's GM technology adoption is represented as the following Bellman equation:

$$V^{l}\left(\boldsymbol{\mu}^{l}, \Sigma^{l} \mid \Theta^{l}\right) = \max_{\mathbf{x}^{l}} \left\{ \left(\mathbf{x}^{l\top} \cdot \boldsymbol{\mu}^{l} - \frac{1}{2} \cdot r^{l} \cdot \mathbf{x}^{l\top} \cdot \Sigma^{l} \cdot \mathbf{x}^{l} \right) + \delta \cdot \underset{z_{+}^{l}}{E}\left[V^{l}\left(\boldsymbol{\mu}_{+}^{l}, \Sigma_{+}^{l}\right) \middle| z^{l} \right] \middle| \Theta^{l} \right\}$$

$$\Leftrightarrow V^l\left(S^l \mid \Theta^l\right) = \max_{\begin{bmatrix} x^{CONV,l} \\ x^{GM,l} \end{bmatrix}} \left\{ \begin{array}{l} \left\{ \begin{array}{l} \begin{bmatrix} x^{CONV,l} & x^{GM,l} \end{bmatrix} \cdot \begin{bmatrix} \mu^{CONV,l} \\ \mu^{GM,l} \end{bmatrix} - \frac{1}{2} \cdot r^l \cdot \begin{bmatrix} x^{CONV},l & x^{GM,l} \end{bmatrix} \\ \times \begin{bmatrix} \sigma^2_{CONV,l} & \rho^l_{CONV,GM} \cdot \sqrt{\sigma^2_{CONV,l} \cdot \sigma^2_{GM,l}} \\ \rho^l_{GM,CONV} \cdot \sqrt{\sigma^2_{GM,l} \cdot \sigma^2_{CONV,l}} & \sigma^2_{GM,l} \end{bmatrix} \\ \times \begin{bmatrix} x^{CONV,l} \\ x^{GM,l} \end{bmatrix} \end{array} \right\} \\ +\delta \cdot \underset{z^l_+}{E}\left[V^l\left(S^l_+\right) \mid z^l\right] \end{array} \middle| \Theta^l \right\}, \tag{3.35}$$

where $S^l = \left\{\mu^{CONV,l}, \sigma^2_{CONV,l}, \mu^{GM,l}, \sigma^2_{GM,l}\right\}$ is the state space at the current period for each farm type l. The state space at the next period is $S^l_+ = \left\{\mu^{CONV,l}_+, \sigma^2_{+,CONV,l}, \mu^{GM,l}_+, \sigma^2_{+,GM,l}\right\}$. Then, elements in S^l and S^l_+ are such that satisfy the following Kalman filter algorithm:

$$\begin{bmatrix} \mu^{CONV,l}_+ \\ \mu^{GM,l}_+ \end{bmatrix} = \left[I - \Sigma^l_+ \cdot \left(\boldsymbol{\gamma}^l\right)^{\mathsf{T}} \cdot \left(N^l_+\right)^{-1} \cdot \boldsymbol{\gamma}^l\right] \cdot \left[\begin{bmatrix} \mu^{CONV,l} \\ \mu^{GM,l} \end{bmatrix} + \boldsymbol{\beta}^l \cdot \begin{bmatrix} x^{CONV,l} \\ x^{GM,l} \end{bmatrix}\right] + \Sigma^l_+ \cdot \left(\boldsymbol{\gamma}^l\right)^{\mathsf{T}} \cdot \left(N^l_+\right)^{-1} \cdot \mathrm{z}^l_+, \tag{3.36}$$

$$\Sigma^l_+ = \Sigma^l + M^l - \left[\Sigma^l + M^l\right] \cdot \left(\boldsymbol{\gamma}^l\right)^{\mathsf{T}} \cdot \left[\boldsymbol{\gamma}^l \cdot \left[\Sigma^l + M^l\right] \cdot \left(\boldsymbol{\gamma}^l\right)^{\mathsf{T}} + N^l_+\right]^{-1} \boldsymbol{\gamma}^l \cdot \left[\Sigma^l + M^l\right]. \tag{3.37}$$

The variance-covariance matrices for each farm type $l \in \{EARLY, INTER, LATE\}$ are

$$\Sigma^l = \begin{bmatrix} \sigma^2_{CONV,l} & \rho^l_{CONV,GM} \cdot \sqrt{\sigma^2_{CONV,l} \cdot \sigma^2_{GM,l}} \\ \rho^l_{GM,CONV} \cdot \sqrt{\sigma^2_{GM,l} \cdot \sigma^2_{CONV,l}} & \sigma^2_{GM,l} \end{bmatrix}$$

at the current period, and

$$\Sigma^l_+ = \begin{bmatrix} \sigma^2_{+,CONV,l} & \rho^l_{CONV,GM,+} \cdot \sqrt{\sigma^2_{+,CONV,l} \cdot \sigma^2_{+,GM,l}} \\ \rho^l_{GM,CONV,+} \cdot \sqrt{\sigma^2_{+,GM,l} \cdot \sigma^2_{+,CONV,l}} & \sigma^2_{+,GM,l} \end{bmatrix}$$

at the next period. In addition, we have

$$M^l = \begin{bmatrix} \sigma^2_{v^{CONV,l}} & 0 \\ 0 & \sigma^2_{v^{GM,l}} \end{bmatrix},$$

$$N^l = \begin{bmatrix} \sigma^2_{q^{CONV,l}} & 0 & 0 & 0 \\ 0 & \sigma^2_{y^{CONV,l}} & 0 & 0 \\ 0 & 0 & \sigma^2_{q^{GM,l}} & 0 \\ 0 & 0 & 0 & \sigma^2_{y^{GM,l}} \end{bmatrix}, \text{ and } N^l_+ = \begin{bmatrix} \sigma^2_{q_+^{CONV,l}} & 0 & 0 & 0 \\ 0 & \sigma^2_{y_+^{CONV,l}} & 0 & 0 \\ 0 & 0 & \sigma^2_{q_+^{GM,l}} & 0 \\ 0 & 0 & 0 & \sigma^2_{y_+^{GM,l}} \end{bmatrix}.$$

For each farm type l, the parameter space $\Theta^l = \left\{ r^l, \boldsymbol{\beta}^l, \boldsymbol{\gamma}^l \right\}$ includes the Arrow-Pratt measure of absolute risk-aversion coefficient r^l from the reward function, a 2-by-2 matrix parameter $\boldsymbol{\beta}^l$ form the system equation, and a 4-by-2 parameter matrix $\boldsymbol{\gamma}^l$ from the measurement equation of the disaggregate DP model.

Denoting the value function given the state space S^l under the given Θ^l as $V^l\left(S^l \mid \Theta^l\right)$, the l-type adopter's optimal policy functions are obtained from solving Bellman equation in (3.35), being presented as $\mathbf{x}^{l*}\left(S^l \mid \Theta^l\right) = \left[x^{CONV,l*}\left(S^l \mid \Theta^l\right) \quad x^{GM,l*}\left(S^l \mid \Theta^l\right) \right]^\top$ given Θ^l for each farm type l. The overall algorithm for dynamic optimization and estimation strategy is basically the same as for the aggregate model, as discussed in the previous section. Further details are provided in Chapter 4.

Chapter 4 : Data and Methods

This chapter is composed of two major sections. The first section presents data used for empirical research applying the conceptual structural DP adoption model developed in Chapter 3. Data used for the aggregate model is introduced first and followed by data used for the disaggregate model. The second section discusses numerical methods used for solving the DP models conditional on a set of parameters and provides estimation strategy for the parameters of the DP adoption model. An algorithm is devised for considering both dynamic optimization and parameter estimation. The collocation method is used to obtain a numerical solution for the DP adoption model. And a minimum distance estimator is used for estimation.

4.1.Data

4.1.1. Data for the Aggregate Model

For the empirical application of the conceptual model of GM corn seed adoption, this study relies on various data sources on the U.S. corn seed market. The majority of information comes from an extensive survey data collected by DMR. The DMR data are annual survey data from a sample of U.S. corn farmers between 2000 and 2007 across 279 Crop Reporting Districts (CRDs) in 48 states.[14] First of all, the DMR data provides farm-level information on purchased corn hybrids with information on associated GM technologies including herbicide tolerance (HT), insect resistance (IR), and stacked versions of HT and IR. For each GM technology, farm-level information on seed costs and planted acreage are provided with other farm attributes such as farm size and location (longitude and latitude).

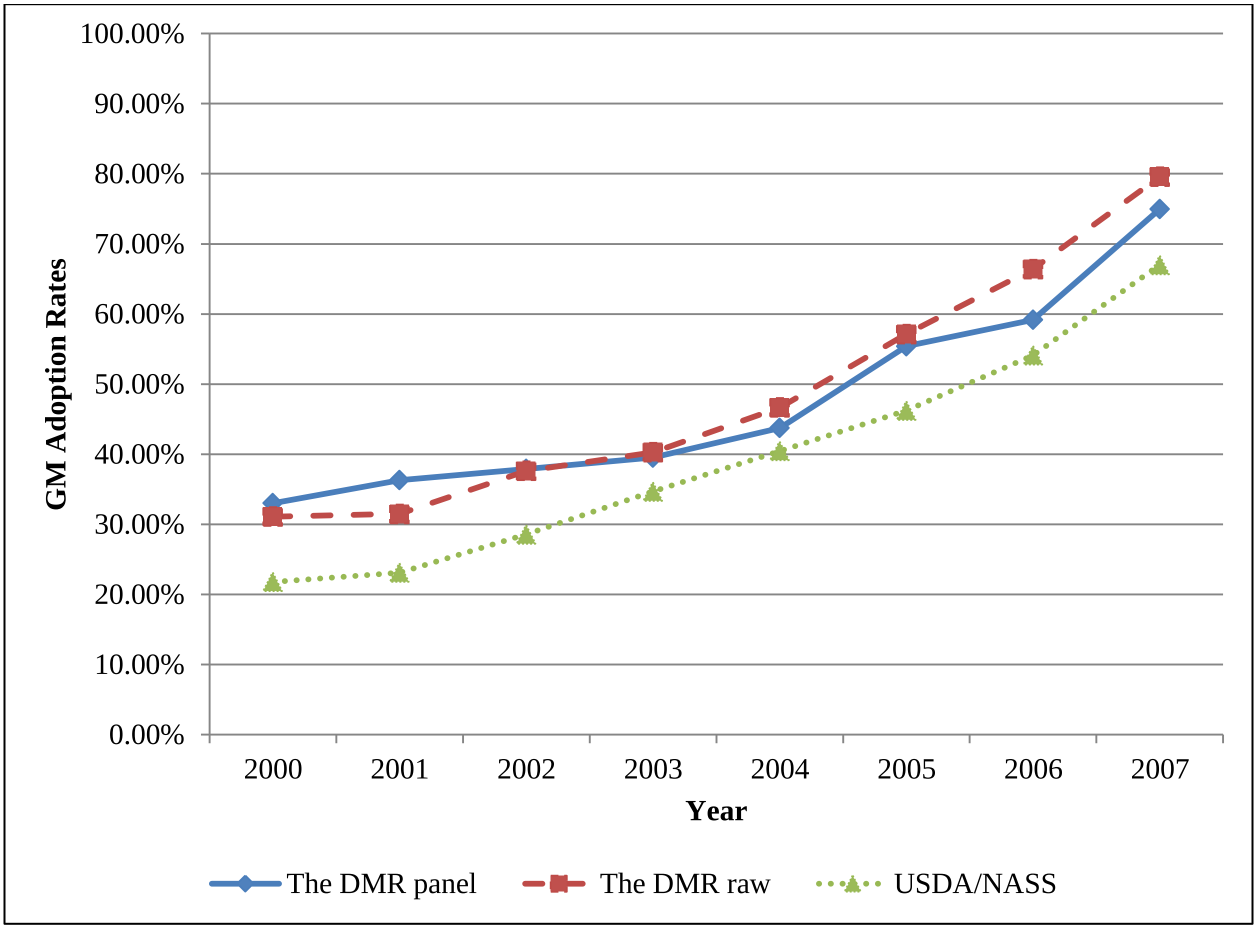
[14] The raw data has 168,862 observations at the plot level on a total of 38,617 farmers.

The DMR dataset is a rotating panel data, where a part of the sampled farmers is replaced every year. As such, it provides an unbalanced panel data. As our conceptual structural DP model concerns GM adoption over time, it will be convenient to focus on a balanced panel data to investigate farmers' sequential adoption behavior. But 175 farmers among 38,617 are surveyed every year in the DMR data. Using observations on these 175 farmers constitutes a panel data. These farmers are all located in the U.S. Corn Belt (as are 84.07% of all farmers surveyed by DMR).

The Corn Belt covers 51 CRDs in 11 states: Illinois, Indiana, Iowa, Kentucky, Michigan, Minnesota, Missouri, Nebraska, Ohio, South Dakota, and Wisconsin. Finally, eliminating farmers that have missing or inconsistent data, the panel data reduces form 175 farmers to 136 farmers. The first question is: Are the GM adoption rates among these farmers similar to the adoption rates observed among other farmers?

Figure 4.1 compares adoption statistics from the DMR panel data versus USDA data (obtained from USDA/NASS). GM corn adoption rates of planted acres in the U.S. Corn Belt from USDA/NASS (2011) is used to check whether there may exist a selectivity bias between the DMR population/panel data and national survey data provided by USDA/NASS. Figure 4.1 shows how the pattern of GM corn adoption from each source differs across data sources. Adoption rates from the DMR population/panel data are a little higher than rates from USDA/NASS (by about 10 percent), but the overall patterns are similar during the same survey period. Thus, Figure 4.1 indicates that farmers surveyed by the DMR represent the typical GM adoption pattern observed by USDA/NASS and that there is no strong selectivity bias in using the DMR panel data in the analysis of GM adoption.

Figure 4.1: Selectivity Bias between the DMR and USDA/NASS



Source: The DMR survey data and USDA/NASS (2011)

Note: Y-axis indicates adoption rates of planted acres to GM seed

Table 4.1 reports descriptive statistics on GM adoption rates and other variables from the DMR panel dataset composed of 136 farmers in the U.S. Corn Belt, which includes farm-level information on acreage planted with conventional seeds and GM seeds, neighbors' acreage planted with each technology, and seed cost paid by each farmer for each technology from 2000 to 2007. On average, the lagged adoption rates of GM seed both for each farmer and for his/her neighbors, x_{it-1}^{GM} and y_{it-1}^{GM} are lower than the current adoption rates x_{it}^{GM} and y_{it}^{GM}, respectively. This shows an increasing adoption pattern of GM technology.

Table 4.1: Descriptive Statistics of the DMR Panel Data, 2000-2007, the U.S. Corn Belt

Variable	Description	Number of Obs.[a/]	Mean	S. D.	Min.	Max.
Acreage (unit: acres in thousands)						
J_{it}	Farmer i's total acreage in year t	1,088	15.7	17.8	0.8	249.9
J_{it}^{CONV}	Farmer i's acreage sown to conventional seed in year t	1,088	8.3	14.1	0.0	184.6
J_{it}^{GM}	Farmer i's acreage sown to GM seed in year t	1,088	7.4	13.1	0.0	249.9
G_{it}	Farmer i's neighbors' total acreage in year t	1,088	1,161.6	555.2	24.3	2,245.0
G_{it}^{CONV}	Farmer i's neighbors' acreage sown to conventional seed in year t	1,088	572.4	333.3	17.9	1,425.8
G_{it}^{GM}	Farmer i's neighbors' acreage sown to GM seed in year t	1,088	589.2	459.0	4.1	2,135.4
Adoption Rate (unit: %)						
x_{it}^{CONV}	Farmer i's conventional seed adoption rate in year t	1,088	52.50	40.92	0.00	100.00
x_{it}^{GM}	Farmer i's GM seed adoption rate in year t	1,088	47.50	40.92	0.00	100.00
x_{it-1}^{CONV}	Farmer i's conventional seed adoption rate in year $t-1$	952	56.42	40.21	0.00	100.00
x_{it-1}^{GM}	Farmer i's GM seed adoption rate in year $t-1$	952	43.58	40.21	0.00	100.00
y_{it}^{CONV}	Farmer i's neighbors' conventional seed adoption rate in year t	1,088	53.00	22.12	4.17	95.70
y_{it}^{GM}	Farmer i's neighbors' GM seed adoption rate in year t	1,088	47.00	22.12	4.30	95.83
y_{it-1}^{CONV}	Farmer i's neighbors' conventional seed adoption rate in year $t-1$	952	57.13	19.96	6.63	95.70
y_{it-1}^{GM}	Farmer i's neighbors' GM seed adoption rate in year $t-1$	952	42.87	19.96	4.30	93.37
Seed price (unit: \$/acre)[b/]						
p_{it}^{CONV}	Conventional seed price paid by farmer i in year t	808	32.0	5.4	11.9	47.7
p_{it}^{GM}	GM seed price paid by farmer i in year t	737	39.9	7.0	14.1	57.8

Note: [a/] The DMR balanced panel data has observations of 1,088 (136 farmers times 8 years from 2000 through 2007). As for lagged variables x_{it-1}^{CONV}, x_{it-1}^{GM}, y_{it-1}^{CONV}, and y_{it-1}^{GM}, the number is 952 (136 farmers times 7 years).

[b/] The original unit in the DMR dataset is \$/80,000 kernel bag. The unit is converted into \$/acre assuming 80,000 kernel bag corresponds to 2.7 acre following Lamkey (2010).

Note that our DP model involves imperfect state information where state variables are unobservable. That is, farmer i's perceived per-acre profitability π_{it}^{k} for each technology k = { $CONV$, GM } is not known for sure at planting time (when farmers choose the seed type). However, it is necessary to quantify them in order to solve Bellman equations numerically. To quantify farmer i's per-acre profitability π_{it}^{k} for each technology $k = \{CONV, GM\}$ at time period $t = \{2000, ..., 2007\}$, we first specify the state equation:

$$\pi_{it}^{k} = RP_{it} \times q_{it}^{k} - p_{it}^{k} + CS_{it}^{k}, \tag{4.1}$$

where π_{it}^{k} (\$/acre) denotes farmer i's per-acre farm profit from planting the k-technology corn seed in year t. RP_{it} (\$/bushel) stands for corn price in year t. q_{it}^{k} is yield (bushels per acre) for the k-technology seed. And p_{it}^{k} (\$/acre) is the seed cost for the k-technology seed. Finally, CS_{it}^{k} (\$/acre) denotes the cost associated with planting the k-technology seed. In our analysis, we consider CS_{it}^{k} as measuring variable cost. This means that fixed costs (e.g., associated with land or capital) are treated as constant and that π_{it}^{k} in (4.1) denotes profit over variable cost.

While the DMR data covers seed cost p_{it}^{k}, it does not provide information about other costs of production. Thus, we have to rely on other sources of information to evaluate these other costs. For corn price, RP_{it}, we use annual corn price received by farmers, as reported by USDA/NASS.[15]

As noted, we need data on variable cost (CS_{it}^{k}) for our analysis. Importantly, this cost can vary across technologies. Indeed, GM technologies are associated with lowered usage of herbicide or insecticide and reduced uses of labor and fuel (e.g., when farmers plant GM corn

[15] http://quickstats.nass.usda.gov/

using minimum or zero tillage). To estimate these costs, we use data provided by the National Center for Food and Agricultural Policy (NCFAP); Carpenter and Gianessi (2002), Sankala and Blumenthal (2003; 2006), and Johnson et al. (2008).[16]

Yields for conventional and GM corn seed, q_{it}^{CONV} and q_{it}^{GM} are obtained from field experiment data conducted at Agricultural Research Stations (ARS) in the state of Wisconsin by the University of Wisconsin-Madison. We rely on data from Arlington, WI, located at the Northern part of the Corn Belt. These data provide annual yield information for conventional seed and for GM seed between 1990 and 2010. We assume yield information for conventional seed and GM seed in Arlington, WI represent yield information for each technology in the Corn Belt.[17] And as discussed in Chapter 3, we will use the lagged-one-year yield for technology k, q_{it-1}^{k}, as the observable measurement associated with individual learning for the *k*-th technology.

We combine data from the DMR panel dataset and other sources to generate information about profit π_{it}^{k} in (4.1) for each year and region (at the CRD level when possible or at the state level when CRD data are unavailable). Table 4.2 summarizes the results on farm profit for each technology $k = \{CONV, GM\}$ between 2000 and 2007. The mean and variance of profit for each technology k are used for quantifying the state space composed of four sufficient statistics (the mean and variance of the distribution of π_{it}^{k}) given the information set I_{it} using the Kalman filter, as discussed in Chapter 3: μ^{CONV}, σ_{CONV}^{2}, μ^{GM}, and σ_{GM}^{2}.

[16] Annual summary can be found on Brookes and Barfoot (2011).

[17] This may be a strong assumption as the agro-climatic conditions are not same across CRDs in the U.S. Corn-Belt. However, no sources provide yield information for conventional seed and GM seed with extensive observations; for example, USDA/NASS provide yield information for each year at the county levels (http://quickstats.nass.usda.gov), but there are no distinctions between conventional seed and GM seed. The experimental data provided by UW-Madison is the only available source providing GM trait-specific yield information with large scale data.

Table 4.2: Summary of Variables for the Per-acre Profitability by Technology, 2000-2007

Variable	Description	unit	Data Source	Number of Obs.	Mean	S. D.	Min.	Max.
π_{it}^{CONV}	Farm profit from CONV seed	($/acre)		808	455.66	143.93	307.31	930.89
π_{it}^{GM}	Farm profit from GM seed	($/acre)		737	529.81	188.37	312.86	966.88
RP_{it} [a/]	Received Price of Corn, Grain	($/bushel)	USDA/NASS[b/]	1,088	2.47	0.76	1.61	4.39
q_{it}^{CONV}	Yield for CONV seed	(bushel/acre)	UW-Madison[c/]	1,088	208.29	12.56	185.76	220.65
q_{it}^{GM}	Yield for GM seed	(bushel/acre)	UW-Madison[c/]	1,088	213.46	12.42	189.69	228.70
p_{it}^{CONV}	Seed price for CONV seed	($/acre)	DMR[d/]	808	31.96	5.35	11.85	47.67
p_{it}^{GM}	Seed price for GM seed	($/acre)	DMR[d/]	737	39.95	6.98	14.07	57.78
CS_{it}^{CONV} [f/]	Cost saving by CONV seed	($/acre)	NCFAP[e/]	808	0.00	0.00	0.00	0.00
CS_{it}^{GM}	Cost saving by GM seed	($/acre)	NCFAP[e/]	737	21.52	12.05	7.00	48.22

Note: i is farmer index and t is year index between 2000 and 2007.

[a/] RP_{it} is assumed to be same for conventional seed and for GM seed.

[b/] DMR: the DMR panel dataset (136 farmers at the U.S. Corn Belt),

[c/] USDA/NASS: Quick Stats 2.0 survey data available from: http://quickstats.nass.usda.gov/

[d/] UW-Madison: Field experiments at the UW-Madison,

[e/] NCFAP: National Center for Food and Agricultural Policy, Brookes and Barfoot (2011).

[f/] $CS_{it}^{CONV} = 0$.

In addition, we estimate the correlation coefficient between yield of conventional seed and yield of GM seed $\rho_{CONV,GM,t}$ from 1999 to 2007. This is used to evaluate the covariance term used in the Kalman filter in Section 3.3.1 and the distribution of farmers' payoff in Chapter 5 and Chapter 6.

Estimation of the moments of yield is done as follows. We consider a simple ordinary least-squares (OLS) regression model as follows:

$$Yield_k = \alpha_k + \beta_k \cdot Year + e_k, \tag{4.2}$$

where $Yield_k$ is the yield information for the k-technology seed, $Year$ denotes a time-trend variable reflecting technological progress, β_k is the parameter to be estimated for each technology k, α_k is an intercept, and e_k is an error term with zero mean and a variance $\sigma_{e_k}^2$ for $k = \{CONV, GM\}$. By regressing $Yield_k$ on $Year$ and intercept, we get estimates $\hat{\beta}_k$ and $\hat{\alpha}_k$. Residuals are calculated as $\hat{e}_k = Yield_k - \hat{\beta}_k \cdot Year - \hat{\alpha}_k$ for each technology k. Then, the variance and covariance for the k-seed yield are obtained for each year t by

$$\mathrm{var}\left(Yield_{CONV,t}\right) = E\left[\hat{e}_{CONV,t}^2\right], \tag{4.3}$$

$$\mathrm{var}\left(Yield_{GM,t}\right) = E\left[\hat{e}_{GM,t}^2\right], \tag{4.4}$$

$$\mathrm{cov}\left(Yield_{CONV,t}, Yield_{GM,t}\right) = E\left[\hat{e}_{CONV,t} \cdot \hat{e}_{GM,t}\right]. \tag{4.5}$$

In (4.5), there can be mismatches in dimensions between $\hat{e}_{CONV,t}$ and $\hat{e}_{GM,t}$ as the number of observations for conventional seed and for GM seed are not identical for each year t. We match dimensions between conventional seeds and GM seeds by sampling residuals at the smaller number between two seeds. Then, we simulate 10,000 times so as to calculate the covariance at all possible combinations of sampling. Finally, using (4.3)-(4.5), we obtain the correlation coefficient between yield of conventional seed and yield of GM seed as follows

$$\rho_{CONV,GM,t} = \frac{\operatorname{cov}\left(Yield_{CONV,t}, Yield_{GM,t}\right)}{\sqrt{\operatorname{var}\left(Yield_{CONV,t}\right)} \cdot \sqrt{\operatorname{var}\left(Yield_{GM,t}\right)}}. \tag{4.6}$$

The estimated correlation, $\rho_{CONV,GM,t}$, is then used in evaluating the covariance component in the Kalman filter algorithm as discussed in Section 3.3.1.2. Table 4.3 reports estimated conditional moments.

Table 4.3: Moments Estimation of Corn Yield, 1999–2007, Arlington, WI

Variable	**Description**	**Estimate on Avg.**
$\operatorname{var}\left(Yield_{CONV,t}\right)$	Variance of CONV yield	381.39
$\operatorname{var}\left(Yield_{GM,t}\right)$	Variance of GM yield	375.06
$\operatorname{cov}\left(Yield_{CONV,t}, Yield_{GM,t}\right)$	Covariance between CONV yield and GM yield	140.47
$\rho_{CONV,GM,t}$	Corr. Coefficient between CONV yield and GM yield	0.2948

Source: Field experiments, 1990-2010 at University of Wisconsin-Madison.
Note: The unit of corn yield is (bushel/acre).

The DP model for the GM technology adoption is solved at the aggregate model first, where we assume that a representative farmer makes the adoption decisions. Table 4.4 reports descriptive statistics of variables associated with the aggregate adoption model.

Table 4.4: Descriptive Statistics of Variables for the Aggregate GM Adoption Model, 2000-2007

Variable	Description	unit	Number of Obs.	Mean	S. D.	Min.	Max.
Reward Function							
x_{it}^{CONV}	Own adoption rates for CONV		1,088	0.52	0.41	0.00	1.00
x_{it}^{GM}	Own adoption rates for GM		1,088	0.48	0.41	0.00	1.00
$\rho_{CONV,GM,t}$	Correlation coefficient between CONV and GM		1,088	0.29	0.23	0.00	0.71
System Equation							
π_{it}^{CONV}	Approximated per-acre profitability for CONV	($/acre)	808	455.66	143.93	307.31	930.89
π_{it}^{GM}	Approximated per-acre profitability for GM	($/acre)	737	529.81	188.37	312.86	966.88
Measurement Equation: z_{it}							
q_{it-1}^{CONV}	Yield of CONV at t-1	(Bushel/acre)	1,088	208.78	13.00	185.76	221.96
y_{it-1}^{CONV}	Neighbors' adoption rates for CONV at t-1		952	0.57	0.20	0.07	0.96
q_{it-1}^{GM}	Yield of GM at t-1	(Bushel/acre)	1,088	214.08	12.82	189.69	228.70
y_{it-1}^{GM}	Neighbors' adoption rates for GM at t-1		952	0.43	0.20	0.04	0.93
Role of Random Shock: z_{it+1}							
q_{it}^{CONV}	Yield of CONV at t	(Bushel/acre)	1,088	208.29	12.56	185.76	220.65
y_{it}^{CONV}	Neighbors' adoption rates for CONV at t		1,088	0.53	0.22	0.04	0.96
q_{it}^{GM}	Yield of GM at t	(Bushel/acre)	1,088	213.46	12.42	189.69	228.70
y_{it}^{GM}	Neighbors' adoption rates for GM at t		1,088	0.47	0.22	0.04	0.96

4.1.2. Data for the Disaggregate Model

At the disaggregate model, farmers in the DMR panel dataset are classified into three sub-groups according to their observed adoption patterns. Denoting farm type by $l = \{EARLY, INTER, LATE\}$, data are obtained for the three sub-groups from the 136 farmers in the DMR panel dataset.

In our disaggregate analysis, we assume that farmers are homogeneous within each group, although they can differ across groups. In principle, we can allow for any heterogeneity across groups. We will focus our attention on two issues: heterogeneity in social learning and heterogeneity in risk preferences. For example, we will investigate whether the reliance on social learning varies across farm types. This is a relevant issue since early adopters have few neighbors they can use to learn about GM technology. Alternatively, late adopters have many neighbors they can learn from. This indicates that the prospects for social learning would vary between early and late adopters. But our investigation goes one step further: it asks whether there may be heterogeneity among farmers on how much they rely on social learning (versus individual learning) in their GM adoption decisions. Could it be that farmers who rely less on social learning tend to self-select into being early adopters? Alternatively, could it that farmers who rely more on social interactions tend to self-select into being late adopters? In these cases, heterogeneity in preferences toward information externalities would affect adoption rates both at the disaggregate models and at the aggregate model. And note that the same comments would apply to heterogeneity in risk preferences.

Descriptive statistics of each sub-group for the early-, the intermediate-, and the late-adopter are in Table 4.5, in Table 4.6, and in Table 4.7, respectively.

Table 4.5: Descriptive Statistics of the Sub-Group for the Early Adopter's GM Adoption Model, 2000-2007

Variable $l=\{EARLY\}$	**Description**	**unit**	**Number of Obs.**	**Mean**	**S. D.**	**Min.**	**Max.**
Reward Function							
$x_{it}^{CONV,l}$	Own adoption rates for CONV		240	0.18	0.25	0.00	1.00
$x_{it}^{GM,l}$	Own adoption rates for GM		240	0.82	0.25	0.00	1.00
$\rho_{CONV,GM,t}^{l}$	Correlation coefficient between CONV and GM		240	0.29	0.23	0.00	0.71
System Equation							
$\pi_{it}^{CONV,l}$	Approximated per-acre profitability for CONV	($/acre)	113	448.36	142.17	310.92	915.56
$\pi_{it}^{GM,l}$	Approximated per-acre profitability for GM	($/acre)	230	512.18	175.65	325.65	966.88
Measurement Equation: z_{it}^{l}							
$q_{it-1}^{CONV,l}$	Yield of CONV at t-1	(Bushel/acre)	240	208.78	13.02	185.76	221.96
$y_{it-1}^{CONV,l}$	Neighbors' adoption rates for CONV at t-1		210	0.51	0.19	0.08	0.93
$q_{it-1}^{GM,l}$	Yield of GM at t-1	(Bushel/acre)	240	214.08	12.84	189.69	228.70
$y_{it-1}^{GM,l}$	Neighbors' adoption rates for GM at t-1		210	0.49	0.19	0.07	0.92
Role of Random Variables: z_{it+1}^{l}							
$q_{it}^{CONV,l}$	Yield of CONV at t	(Bushel/acre)	240	208.29	12.59	185.76	220.65
$y_{it}^{CONV,l}$	Neighbors' adoption rates for CONV at t		232	0.19	0.10	0.07	0.40
$q_{it}^{GM,l}$	Yield of GM at t	(Bushel/acre)	240	213.46	12.44	189.69	228.70
$y_{it}^{GM,l}$	Neighbors' adoption rates for GM at t		232	0.81	0.10	0.60	0.93

Table 4.6: Descriptive Statistics of the Sub-Group for the Intermediate Adopter's GM Adoption Model, 2000-2007

Variable $l = \{INTER\}$	**Description**	**unit**	**Number of Obs.**	**Mean**	**S. D.**	**Min.**	**Max.**
Reward Function							
$x_{it}^{CONV,l}$	Own adoption rates for CONV		784	0.43	0.38	0.00	1.00
$x_{it}^{GM,l}$	Own adoption rates for GM		784	0.57	0.38	0.00	1.00
$\rho_{CONV,GM,t}^{l}$	Correlation coefficient between CONV and GM		784	0.29	0.23	0.00	0.71
System Equation							
$\pi_{it}^{CONV,l}$	Approximated per-acre profitability for CONV	($/acre)	544	455.22	148.36	307.31	926.07
$\pi_{it}^{GM,l}$	Approximated per-acre profitability for GM	($/acre)	624	516.84	180.88	312.86	966.88
Measurement Equation: z_{it}^{l}							
$q_{it-1}^{CONV,l}$	Yield of CONV at t-1	(Bushel/acre)	784	208.78	13.00	185.76	221.96
$y_{it-1}^{CONV,l}$	Neighbors' adoption rates for CONV at t-1		686	0.53	0.20	0.07	0.93
$q_{it-1}^{GM,l}$	Yield of GM at t-1	(Bushel/acre)	784	214.08	12.82	189.69	228.70
$y_{it-1}^{GM,l}$	Neighbors' adoption rates for GM at t-1		686	0.47	0.20	0.07	0.93
Role of Random Variables: z_{it+1}^{l}							
$q_{it}^{CONV,l}$	Yield of CONV at t	(Bushel/acre)	784	208.29	12.57	185.76	220.65
$y_{it}^{CONV,l}$	Neighbors' adoption rates for CONV at t		768	0.43	0.10	0.23	0.57
$q_{it}^{GM,l}$	Yield of GM at t	(Bushel/acre)	784	213.46	12.42	189.69	228.70
$y_{it}^{GM,l}$	Neighbors' adoption rates for GM at t		768	0.57	0.10	0.43	0.77

Table 4.7: Descriptive Statistics of the Sub-Group for the Late Adopter's GM Adoption Model, 2000-2007

Variable $l=\{LATE\}$	**Description**	**unit**	**Number of Obs.**	**Mean**	**S. D.**	**Min.**	**Max.**
Reward Function							
$x_{it}^{CONV,l}$	Own adoption rates for CONV		1,088	0.52	0.41	0.00	1.00
$x_{it}^{GM,l}$	Own adoption rates for GM		1,088	0.48	0.41	0.00	1.00
$\rho_{CONV,GM,t}^{l}$	Correlation coefficient between CONV and GM		1,088	0.29	0.23	0.00	0.71
System Equation							
$\pi_{it}^{CONV,l}$	Approximated per-acre profitability for CONV	($/acre)	808	455.66	143.93	307.31	930.89
$\pi_{it}^{GM,l}$	Approximated per-acre profitability for GM	($/acre)	737	529.81	188.37	312.86	966.88
Measurement Equation: z_{it}^{l}							
$q_{it-1}^{CONV,l}$	Yield of CONV at t-1	(Bushel/acre)	1,088	208.78	13.00	185.76	221.96
$y_{it-1}^{CONV,l}$	Neighbors' adoption rates for CONV at t-1		952	0.57	0.20	0.07	0.96
$q_{it-1}^{GM,l}$	Yield of GM at t-1	(Bushel/acre)	1,088	214.08	12.82	189.69	228.70
$y_{it-1}^{GM,l}$	Neighbors' adoption rates for GM at t-1		952	0.43	0.20	0.04	0.93
Role of Random Variables: z_{it+1}^{l}							
$q_{it}^{CONV,l}$	Yield of CONV at t	(Bushel/acre)	1,088	208.29	12.56	185.76	220.65
$y_{it}^{CONV,l}$	Neighbors' adoption rates for CONV at t		1,064	0.53	0.13	0.25	0.66
$q_{it}^{GM,l}$	Yield of GM at t	(Bushel/acre)	1,088	213.46	12.42	189.69	228.70
$y_{it}^{GM,l}$	Neighbors' adoption rates for GM at t		1,064	0.47	0.13	0.34	0.75

From Table 4.4 and Table 4.7, the selected late adopter's sub-group is almost identical with the group for the representative farmer at the aggregate adoption model except for the statistics of neighbors' adoption rates for GM technology at t, y_{it}^{GM}. The DP model is applied for a farmer in each of the l-type disaggregate model. Summary statistics for each l-type farmer's economic variables are presented in Table 4.8.

Table 4.8: Summary for Selected Adopters at the Disaggregate models

Variable	Description	EARLY	INTER	LATE
N^l	Number of Farmers in the l sub-group	30	98	136
Reward Function				
$x_{it}^{CONV,l}$	Own adoption rates for CONV	0.17	0.57	0.83
$x_{it}^{GM,l}$	Own adoption rates for GM	0.83	0.43	0.17
$\rho_{CONV,GM,t}^{l}$ a/	Correlation coefficient between CONV and GM	0.29	0.29	0.29
System Equation				
$\pi_{it}^{CONV,l}$	Approximated per-acre profitability for CONV seed f/	390.05	396.25	499.08
$\pi_{it}^{GM,l}$	Approximated per-acre profitability for GM seed f/	549.13	529.44	676.92
Measurement Equation: z_{it}^{l}				
$q_{it-1}^{CONV,l}$ b/	Yield of CONV seed at t-1 g/	208.78	208.78	208.78
$y_{it-1}^{CONV,l}$	Neighbors' adoption rates for CONV seed at t-1	0.84	0.64	0.74
$q_{it-1}^{GM,l}$ c/	Yield of GM seed at t-1 g/	214.08	214.08	214.08
$y_{it-1}^{GM,l}$	Neighbors' adoption rates for GM seed at t-1	0.16	0.36	0.26
Role of Random Variables: z_{it+1}^{l}				
$q_{it}^{CONV,l}$ d/	Yield of CONV seed at t g/	208.29	208.29	208.29
$y_{it}^{CONV,l}$	Neighbors' adoption rates for CONV seed at t	0.79	0.59	0.70
$q_{it}^{GM,l}$ e/	Yield of GM seed at t g/	213.46	213.46	213.46
$y_{it}^{GM,l}$	Neighbors' adoption rates for GM seed at t	0.21	0.41	0.30

Note: $l = \{EARLY, INTER, LATE\}$

a/ b/ c/ d/ e/ Yield information are same across l sub-groups as the information in Arlington, WI is commonly used.
Unit: f/ (\$/acre) and g/ (Bushel/acre)

4.2. Methods for the DP Solution and the Model Estimation

4.2.1. Algorithm

An empirical application of the DP adoption model to the DMR data requires to combine a dynamic optimization problem and an econometric estimation problem. This integration of optimization and econometric estimation can be challenging. This section introduces an algorithm that solves the DP adoption model as a nested problem within an econometric model used for parameter estimation.

As illustrated in Figure 4.2, the algorithm is composed of two major loops. The first loop is termed as the Minimum Distance Estimation (MDE) loop, where parameters in the DP system are estimated using a nonlinear minimum distance estimator (Greene, 2003; Manski, 1988). The second loop is the Dynamic Programming (DP) loop, where the DP adoption models are numerically solved relying on the collocation method (Miranda and Fackler, 2002). Our algorithm implements solving Bellman equations nested within the model estimation.

For each DP adoption model - the aggregate model and the three l-type disaggregate models for $l = \{EARLY, INTER, LATE\}$, the MDE loop begins with considering the parameter space $\Theta^l = \{r^l, \boldsymbol{\beta}^l, \boldsymbol{\gamma}^l\}$, whose dimension is 8 for the aggregate model and for the intermediate adopter's model and is 5 for the early adopter's model and for the late adopter's model.[18] Starting with initial guesses about the parameters, Bellman equation is solved conditional on these parameter values, as developed in Chapter 3.

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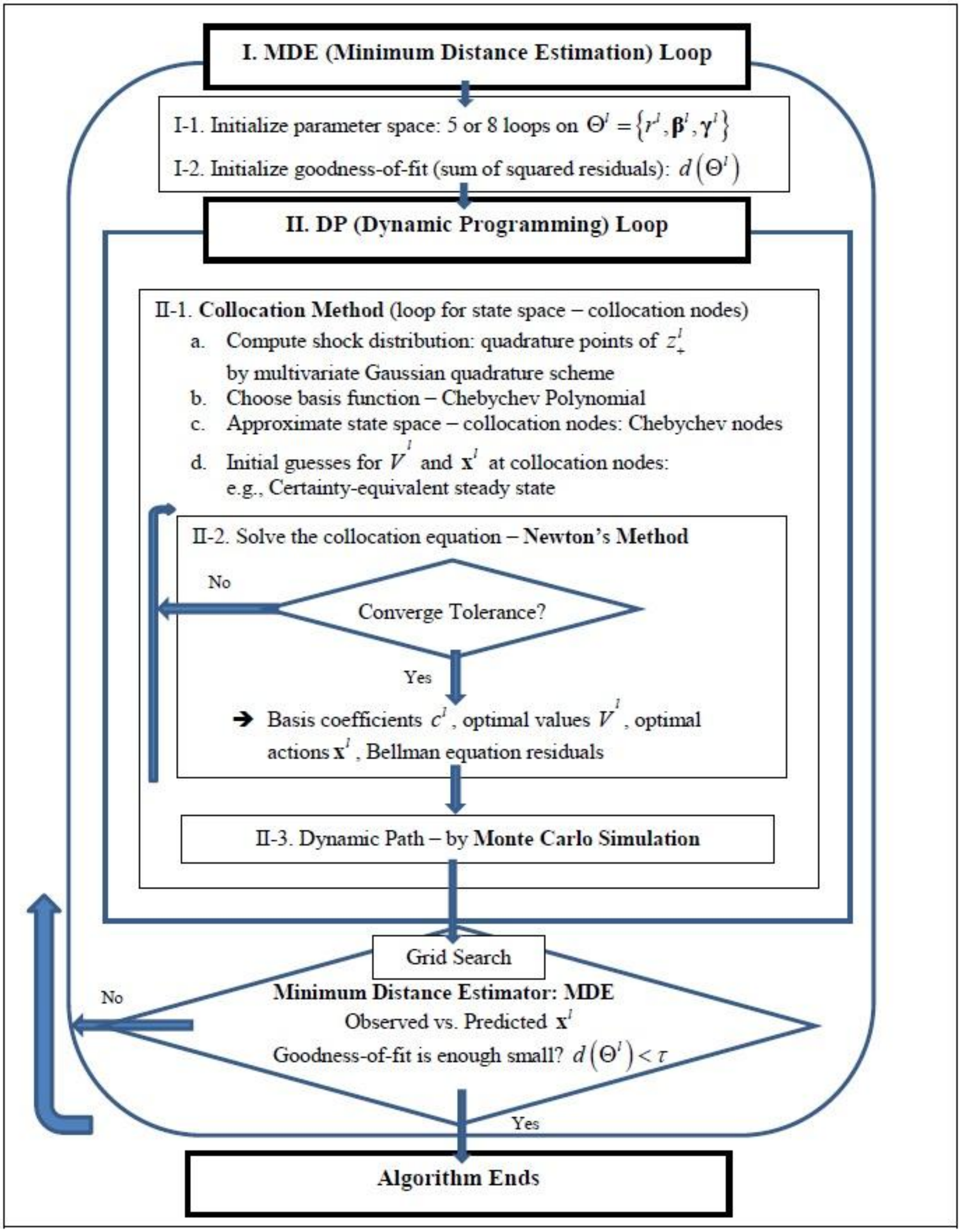
[18] Number 8 comes from $\{r, \beta_{11}, \beta_{22}, \gamma_{11}, \gamma_{21}, \gamma_{31}, \gamma_{32}, \gamma_{42}\}$ for the aggregate model and for the intermediate-type model, and number 5 comes from $\{r, \gamma_{11}, \gamma_{21}, \gamma_{32}, \gamma_{42}\}$ for the early- and the late- type disaggregate models. This issue is discussed in Section 4.2.3.

Figure 4.2: The Flow Chart of the Algorithm



The DP solution gives information about adoption rates that are then matched with observable adoption data, and a goodness-of-fit statistic is obtained: sum of squared deviations denoted by $d\left(\Theta^{l}\right)$.

For given parameters Θ^{l}, the DP loop nested in the MDE loop is implemented. The DP models are constructed as infinite time-horizon problems over the continuous state space. Under stationarity, the DP model is a functional equation whose unknowns are the value functions. In the absence of analytical closed form solution, numerical methods are considered to solve Bellman equations. The DP loop uses the collocation method to obtain numerical solutions (Miranda and Fackler, 2002).

Following Miranda and Fackler (2002), the DP loop itself consists of three sub-processes. The first sub-process is to transform the infinite dimensional functional equation problem (Bellman equation) into a simpler finite dimensional root-finding problem using the collocation method. For empirical tractability, the stochastic part of the Bellman equation is replaced by the multivariate Gaussian quadrature scheme. The DP loop chooses Chebychev polynomial as the basis function, being used for approximating the functional equation. Then, each dimension in the continuous state space (composed of the conditional mean and variance of the unobservable per-acre profitability as given by the Kalman filter), is discretized using the collocation nodes. Initial guesses for the collocation function $V\left(c^{l} \mid \Theta^{l}\right)$ and optimal choices $\mathbf{x}^{l}$ are selected in order to solve collocation equations in terms of collocation coefficients c^{l} s. The DP loop uses values at the certainty-equivalent steady state as initial guesses.

Using the collocation method, the second sub-process is to solve a n-degree nonlinear system equations (Miranda and Fackler, 2002). In our DP models, reward function is represented by the additive mean-variance utility function, and the transition equation for the state space is constructed as the non-linear recursive equations by the Kalman filter. Further, the Chebychev polynomial is non-linear by its structure. This introduces nonlinearity in the DP system. In this context, it is useful to apply the method of policy function iteration using derivatives (e.g., Jacobian matrix of the collocation function). Thus, Newton's method is used for solving the nonlinear collocation equations approximately in the context of root-finding problems. The procedure by Newton's method is iterated until the condition for convergence is met.[19]

The third sub-process implements the dynamic path analysis as a postoptimality analysis (Miranda and Fackler, 2002). The DP models for GM technology adoption are stochastic Bellman equations with the random components on future measurements z_+ and on initial conditions of the state space. Thus, optimal solutions can be affected by changes in initial conditions or the random variables from future observations. Based on optimal approximated value functions and optimal policy functions obtained from Newton's method, the third sub-process evaluates how optimal policy functions (GM adoption rates) evolve over time by given initial conditions. Simple Monte Carlo Simulation is implemented in this process. Based on optimal results from the second sub-process, a sequence of pseudorandom shocks are generated, being applied to the transition equations represented as the Kalman filter. In turn, different adoption rates are obtained in the changed environment, being simulated 10,000 times to get a representative dynamic path for 8 years between 2000 and 2007.

Once solved, the DP results are used in the MDE loop. The simulated (predicted) GM adoption rates are compared with observed adoption rates from the DMR panel dataset. The difference between the simulated GM adoption rates and observed GM adoption rates is calculated from 2000 to 2007. Then, the sum of squared differences is obtained over 8 years,

[19] In our programming, convergence tolerance is $\sqrt{\varepsilon}$ = 1.4901e-08.

$d\left(\Theta^l\right)$. This provides a measure of distance between the model and the data and a useful goodness-of-fit statistic. When $d\left(\Theta^l\right)$ is minimized with respect to Θ^l, then the algorithm ends.[20] Otherwise, the MDE loop restarts with new Θ^l and goes through the DP loop with updated values for the parameters Θ^l. This procedure is performed using the gird search.

4.2.2. Methods for the DP Solution: The Collocation Method

The DP adoption models both at the aggregate and at the disaggregate models are given by Bellman equations (using with sufficient statistics under normality and stationarity, as discussed in Chapter 3). Under stationarity, the infinite time-horizon adoption problems involve solutions of the functional equations whose unknowns are time-invariant value functions. Under normality, the state space is composed of the mean and variance of the unobservable state variables, allowing Bellman equations to be solved under a continuous state space.

In the absence of analytical closed-form solutions for the functional equations, Bellman equations need to be solved numerically. This paper uses the collocation method. The method is known to be flexible and numerically more efficient than other methods such as the linear-quadratic approximation (Miranda and Fackler, 2002). In our paper, the aggregate model and the l-type disaggregate model are identical in its structure. For simplicity, this section explains our numerical methods with a focus on the aggregate model. Bellman equation for the aggregate GM adoption model is described in (3.30), being expressed as

$$V\left(S \mid \Theta\right) = \max_{\mathbf{x}} \left\{ f\left(S, \mathbf{x}\right) + \delta \underset{z_+}{E}\left[V\left(S_+\right) \mid z \right] \middle| \Theta \right\}, \tag{4.7}$$

---

[20] Our model sets up $\tau \in \left[0, 0.06\right]$

where $S=\left\{\mu^{CONV},\sigma^2_{CONV},\mu^{GM},\sigma^2_{GM}\right\}$ denotes the state space composed of the mean and variance of the unobservable profitability π^k for $k=\{CONV,GM\}$. The next period state space is denoted by $S_+=\left\{\mu_+^{CONV},\sigma^2_{+,CONV},\mu_+^{GM},\sigma^2_{+,GM}\right\}$, and the transition equations between S and S_+ are specified by the Kalman filter algorithm as the evolutionary equations between the current conditional moments and their consecutive conditional moments given observable measurements vector z. Adoption rates for each technology k (choice variables) are denoted by a vector $\mathbf{x}=\begin{bmatrix} x^{CONV} & x^{GM} \end{bmatrix}^{\mathrm{T}}$. The additive mean-variance utility function is given by a reward function $f(S,\mathbf{x})$, which is affected both by the state vector S and by the choice vector $\mathbf{x}$. The parameter space is denoted by $\Theta=\{r,\boldsymbol{\beta},\boldsymbol{\gamma}\}$.

The solution of Bellman equation using the collocation method is implemented as follows. First, assuming that the continuous state space S has bounded intervals for each factor in S, the unknown value function under given Θ, $V(S\mid\Theta)$ is approximated as the following linear combination of basis function ϕ_j and its corresponding coefficient c_j

$$V(S\mid\Theta)\approx\sum_{j=1}^{n}c_j\phi_j(S\mid\Theta), \tag{4.8}$$

where n indicates the degree of interpolation. The basis function $\phi_j(.)$ is selected as a known function and plays a role of the approximant for the value function. All the aggregate model and the disaggregate models choose the Chebychev polynomial as a basis function because of its ability to fit any smooth curve well over the continuous state space globally.

By taking the Chebychev polynomial as the basis function ϕ_j, the unknowns to solve are not $V(S \mid \Theta)$ but the basis function coefficients c_j, j = 1, 2, …, n, involving n-nonlinear equation system represented by

$$\sum_{j=1}^{n} c_j \phi_j \left(S_i \mid \Theta\right) = \max_{\mathbf{x}(S_i)} \left\{ f\left(S_i, \mathbf{x}\right) + \delta \sum_{m=1}^{M} \sum_{j=1}^{n} \eta_m c_j \phi_j \left(S_{+i}\right) \middle| \Theta \right\}, \tag{4.9}$$

where S_i is the i-th collocation node among n collocation nodes $\{S_1, S_2, \ldots, S_n\} \subset S$ in the state space. This means that the value function approximant is solved not over all the possible states but over n selected collocation nodes in the discretized state space with function values interpolated by the given basis function. The DP adoption models choose the Chebychev nodes because the Chebychev basis coefficients can be calculated fast at Chebychev nodes (Miranda and Fackler, 2002, p. 122). For numerical tractability, the expected operator in terms of z_+, $E_{z_+}[\cdot]$ in the stochastic Bellman equation is replaced by a discrete approximant $\sum_{m=1}^{M} \eta_m$, where η_1, η_2, …, η_M indicate assumed probabilities for $z_{+,1}$, $z_{+,2}$, …, $z_{+,M}$, respectively, being used as quadrature points.

The n-nonlinear equation system is expressed as the following collocation equation

$$\Phi c = \hat{V}\left(c \mid \Theta\right), \tag{4.10}$$

where Φ denotes the n by n collocation matrix whose i-j element indicates the j-th basis function at the i-th collocation node, representing $\Phi_{ij} = \phi_j\left(S_i \mid \Theta\right)$. Distinguished from the value function $V(S \mid \Theta)$, $V(c \mid \Theta)$ denotes the collocation function evaluated at the collocation node c, and its i-th element is represented by

$$V_i\left(c\,|\,\Theta\right)=\max_{\mathbf{x}(S_i)}\left\{f\left(S_i,\mathbf{x}\right)+\delta\sum_{m=1}^{M}\sum_{j=1}^{n}\eta_m c_j\phi_j\left(S_{+i}\right)\middle|\Theta\right\}. \tag{4.11}$$

Through this process, the collocation equation is represented by a non-linear system of equations being solved numerically. We consider the collocation equation in (4.10) as a root-finding problem of $\Phi c-\hat{V}\left(c\,|\,\Theta\right)=0$ and solve it using Newton's method with the following iterative updating rule

$$c\leftarrow c-\left[\Phi-J_{V(c|\Theta)}\right]^{-1}\left[\Phi c-\hat{V}\left(c\,|\,\Theta\right)\right], \tag{4.12}$$

where $J_{V(c|\Theta)}$ indicates the n-by-n Jacobian of the collocation function $V\left(c\,|\,\Theta\right)$ at the collocation nodes c.

The algorithm combining the DP loop and the MDE loop provides an advanced and refined way to solve dynamic optimization problem with parameter estimation simultaneously. However, it suffers from a significant computational cost. First, in the MDE loop, the dimension of parameters to be estimated amounts to 5 or 8, indicating that at least 5 or 8 loops are programmed in the algorithm. Second, the DP loop nested within the MDE loop also involves a large computational cost. Though the dimension of the state space is moderate to be 4 (the conditional mean and variance of the profitability for each technology), the evaluation points are increased exponentially according to the degree of interpolation n. For example, when n = 10 for each factor in 4-dimensional state space, the number of all possible combinations of nodes is 10^4 for each dimension, being its corresponding collocation grid becomes 10^4-by-4. In addition, the Gaussian quadrature scheme, which is used for discretizing the shock space, also increases the computational cost by involving more loops. As Newton's method is implemented over all enumerated collocation node grid, increments in n will slow down the speed of computation.[21]

Table 4.9 reports initial conditions and numerical assumptions for solving Bellman equations for GM technology adoption using the collocation method. Associated values with the aggregate and the l-type disaggregate adoption models are reported together. The following variables are relevant[22]: farm profitability $\pi_{it}^{k,l}$, the previous year's neighbors adoption rates $y_{it-1}^{k,l}$, the previous year's k-seed yield information $q_{it-1}^{k,l}$, the correlation coefficient among k-seeds $\rho_{CONV,GM,t}$, and the conditional variance of the k-seed yield $\text{var}\left(Yield_{k,t} \mid Year\right)$, for each technology k and group l.

Then, solving the DP loop generates the optimal adoption decisions. For each group (the aggregate model or the l-type disaggregate model), the dimension of the state space and of the action space is identified as 4 and 2, respectively. Initial values necessary for making initial conditions of the state space are assumed to be average values in the starting point 2000. Given guessed initial values for parameters, the state space is approximated using Chebychev nodes. Assuming the state space is bounded, the lower bound and the upper bound for each dimension are assigned by considering minimum and maximum values of the mean and variance of $\pi_{it}^{k,l}$. For the degree of interpolation n, we choose n = 3, making (3^4)-by-4 grid points. Then 3-nodes Chebychev polynomial interpolation is used as a basis function for our model.

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[21] We used MATLAB R2012a (64bit). Though we run the code with the latest version, it took 5,874 seconds (almost 1 hour and 40 minutes) on average just a single simulation using the algorithm.

[22] Note that values in Table 4.9 are downsized. Except for one's own and neighbors' adoption rates, we divide all values by 100 to get down-sized values. This partially helps speed up the running the DP loop.

Table 4.9: Initial Conditions for the DP Loop

Variable	Description	Used variables & Assumptions	AGG	EARLY	INTER	LATE
Definition of dimensions						
ds	Dimension of the state space	$S_{it}^{l} = \left\{ \mu_{it\|t}^{CONV,l}, \sigma_{it\|t,CONV,l}^{2}, \mu_{it\|t}^{GM,l}, \sigma_{it\|t,GM,l}^{2} \right\}$	4	4	4	4
dx	Dimension of the action space	$\mathbf{x}_{it}^{l} = \begin{bmatrix} x_{it}^{CONV,l} & x_{it}^{GM,l} \end{bmatrix}^{\mathrm{T}}$	2	2	2	2
Initial Values						
$y_{it=2000}^{CONV,l}$	Neighbors' CONV adoption rates in 2000	Average of $y_{it=2000}^{CONV,l}$ in 2000	0.69	0.40	0.57	0.66
$y_{it=2000}^{GM,l}$	Neighbors' GM adoption rates in 2000	Average of $y_{it=2000}^{GM,l}$ in 2000	0.31	0.60	0.43	0.34
$q_{it=1999}^{CONV,l}$	CONV yield in 1999	Average of $q_{it=1999}^{CONV,l}$ in 2000	2.22	2.22	2.22	2.22
$y_{it=1999}^{CONV,l}$	Neighbors' CONV adoption rates in 1999	N/A in DMR, approximants less than rates in 2000	0.70	0.50	0.67	0.76
$q_{it=1999}^{GM,l}$	GM yield in 1999	Average of $q_{it=1999}^{GM,l}$ in 2000	2.24	2.24	2.24	2.24
$y_{it=1999}^{GM,l}$	Neighbors' GM adoption rates in 1999	N/A in DMR, approximants less than rates in 2000	0.30	0.50	0.33	0.24
$\rho_{CONV,GM,t=2000}^{l}$	Correlation coefficient between CONV yield and GM yield	Average of $\rho_{CONV,GM,t=2000}^{l}$ in 2000	0.34	0.34	0.34	0.34

Table 4.9: Initial Conditions for the DP Loop (Cont.)

Variable	Description	Used variables & Assumptions	AGG	EARLY	INTER	LATE
Discretization of future measurements distribution: z_{it+1}^{l}						
n_shock	Number of shocks for Gausisian quadrature scheme		2	2	2	2
mu	[1 x ds] Mean vector					
$q_{it-1}^{CONV,l}$	Mean of CONV yield	Average of $q_{it-1}^{CONV,l}$, 2000-2007	2.08	2.08	2.08	2.08
$y_{it-1}^{CONV,l}$	Mean of neighbors' CONV adoption rates	Average of $y_{it-1}^{CONV,l}$, 2000-2007	0.53	0.19	0.43	0.53
$q_{it-1}^{GM,l}$	Mean of GM yield	Average of $q_{it-1}^{GM,l}$, 2000-2007	2.13	2.13	2.13	2.13
$y_{it-1}^{GM,l}$	Mean of neighbors' GM adoption rates	Average of $y_{it-1}^{GM,l}$, 2000-2007	0.47	0.81	0.57	0.47
var	[ds x ds] Positive definite covariance matrix					
$\operatorname{var}\left(Yield_{CONV,t}\right)$	Variance of CONV yield	Average of $\operatorname{var}\left(Yield_{CONV,t}\right)$, 2000-2007	0.04	0.04	0.04	0.04
$y_{it-1}^{CONV,l}$	Variance of neighbors' CONV adoption rates	Variance of $y_{it-1}^{CONV,l}$, 2000-2007	0.05	0.01	0.01	0.02
$\operatorname{var}\left(Yield_{GM,t}\right)$	Variance of GM yield	Average of $\operatorname{var}\left(Yield_{GM,t}\right)$, 2000-2007	0.04	0.04	0.04	0.04
$y_{it-1}^{GM,l}$	Variance of neighbors' GM adoption rates	Variance of $y_{it-1}^{GM,l}$, 2000-2007	0.05	0.01	0.01	0.02
Approximated State Space - Collocation Node						
n	Degree of collocation nodes					
ssmin	Lower bound of the state space: [1 x ds]	Approximants of minimum values				
$\pi_{it}^{CONV,l}$	Minimum value of farm profit for CONV	Minimum of $\pi_{it}^{CONV,l}$, 2000-2007	3.07	3.11	3.07	3.07
$\operatorname{var}\left(\pi_{it}^{CONV,l}\right)$ [a/]	Minimum value of farm profit variance for CONV	Minimum of $\operatorname{var}\left(\pi_{it}^{CONV,l}\right)$, 2000-2007	0.04	0.04	0.04	0.04
$\pi_{it}^{GM,l}$	Minimum value of farm profit for CONV	Minimum of $\pi_{it}^{GM,l}$, 2000-2007	3.13	3.26	3.13	3.13
$\operatorname{var}\left(\pi_{it}^{GM,l}\right)$ [b/]	Minimum value of farm profit variance for GM	Minimum of $\operatorname{var}\left(\pi_{it}^{GM,l}\right)$, 2000-2007	0.04	0.56	0.56	0.56

Note: [a/] $\operatorname{var}\left(\pi_{it}^{CONV,l}\right)=\operatorname{var}\left(Yield_{it}^{CONV,l}\right)\cdot RP_{it}^{2}$

[b/] $\operatorname{var}\left(\pi_{it}^{GM,l}\right)=\operatorname{var}\left(Yield_{it}^{GM,l}\right)\cdot RP_{it}^{2}$

Table 4.9: Initial Conditions for the DP Loop (Cont.)

Variable	Description	Used variables & Assumptions	AGG	EARLY	INTER	LATE
ssmax	Upper bound of the state space: [1 x ds]	Approximants of maximum values				
$\pi_{it}^{CONV,l}$	Maximum value of farm profit for CONV	Maximum of $\pi_{it}^{CONV,l}$, 2000-2007	9.31	9.16	9.26	9.31
$\mathrm{var}\left(\pi_{it}^{CONV,l}\right)$	Maximum value of farm profit variance for CONV	Maximum of $\mathrm{var}\left(\pi_{it}^{CONV,l}\right)$, 2000-2007	0.56	0.04	0.04	0.04
$\pi_{it}^{GM,l}$	Maximum value of farm profit for GM	Maximum of $\pi_{it}^{GM,l}$, 2000-2007	9.67	9.67	9.67	9.67
$\mathrm{var}\left(\pi_{it}^{GM,l}\right)$	Maximum value of farm profit variance for GM	Maximum of $\mathrm{var}\left(\pi_{it}^{GM,l}\right)$, 2000-2007	0.61	0.61	0.61	0.61
Certainty-Equivalent Steady State - initial values for optimal value functions and optimal policies						
Shock (z_{it+1}^{l}) at steady state						
$q_{it-1}^{CONV,l*}$	CONV yield at steady state	Average values of $q_{it-1}^{CONV,l}$, 2000-2007	2.08	2.08	2.08	2.08
$y_{it-1}^{CONV,l*}$	Neighbors' CONV adoption rates at steady state	Average values of $y_{it-1}^{CONV,l}$, 2000-2007	0.53	0.19	0.43	0.53
$q_{it-1}^{GM,l*}$	GM yield at steady state	Average values of $q_{it-1}^{GM,l}$, 2000-2007	2.13	2.13	2.13	2.13
$y_{it-1}^{GM,l*}$	Neighbors' GM adoption rates at steady state	Average values of $y_{it-1}^{GM,l}$, 2000-2007	0.47	0.81	0.57	0.47
State space at steady state						
$\pi_{it}^{CONV,l*}$	Mean of approximate profitability for CONV at steady state	Average values of $\pi_{it}^{CONV,l}$, 2000-2007	4.56	4.48	4.55	4.56
$\mathrm{var}\left(\pi_{it}^{CONV,l}\right)^{*}$	Variance of approximate profitability for CONV at steady state	Average values of $\mathrm{var}\left(\pi_{it}^{CONV,l}\right)$, 2000-2007	0.23	0.23	0.23	0.23
$\pi_{it}^{GM,l*}$	Mean of approximate profitability for GM at steady state	Average values of $\pi_{it}^{GM,l}$, 2000-2007	5.30	5.12	5.17	5.30
$\mathrm{var}\left(\pi_{it}^{GM,l}\right)^{*}$	Variance of approximate profitability for GM at steady state	Average values of $\mathrm{var}\left(\pi_{it}^{GM,l}\right)^{*}$, 2000-2007	0.23	0.23	0.23	0.23
Adoption rates t steady state						
$x_{it}^{CONV,l*}$	CONV adoption rates at steady state	Assumption of zero adoption for CONV	0.00	0.00	0.00	0.00
$x_{it}^{GM,l*}$	GM adoption rates at steady state	Assumption of full adoption for GM	1.00	1.00	1.00	1.00

Also, using the Gaussian quadrature scheme, we discretize the random shock by assigning collocation nodes weights for multivariate normal distribution. Finally, we consider values at the Certainty-Equivalent steady state for initial values for optimal value functions and policy functions in the DP loop.

Following the above schemes, we solve the DP adoption models using Newton's method in the DP loop. As explained in Section 4.2.1, iteration is done until converge tolerance is less than $\sqrt{\varepsilon}$ = 1.4901e-08. The DP loop ends with simulating GM adoption path over 8 years 10,000 times for the postoptimaliy analysis. We use those simulated adoption paths in estimating parameters.

4.2.3. Methods for Model Estimation: Minimum Distance Estimator

The MDE loop is implemented over the DP loop solving the nonlinear system functional equations. Given Θ^l for each farm type $l = \{EARLY, INTER, LATE\}$, the DP loop provides optimal policy function concerning GM technology adoption rates $x^{GM,l*}\left(S^l \mid \Theta^l\right)$ and simulates corresponding GM adoption rates from 2000 through 2007, denoted by $\hat{x}_t^{GM,l}$ for t = 2000, 2001, …, 2007. The basic strategy for parameter estimation is to compare the simulated (predicted) adoption rates $\hat{x}_t^{GM,l}$ with observed GM adoption rates $x_t^{GM,l}$ from the DMR panel dataset. Then, the parameters in Θ^l are estimated by minimizing the distance between the observed adoption path and the simulated adoption path during the same period. This estimation process relies on a minimum-distance estimator (MDE) (Manski, 1988).

Due to the non-linear structure in the reward function as the additive mean-variance utility function and in the transition equation by the Kalman filter, the MDE involves the non-liner regression model as follows (Greene, 2003)

$$x_t^{GM,l} = h\left(x_t^{GM,l}, \Theta^l\right) + \varepsilon_t^l, \tag{4.13}$$

for t = {2000, 2001, …, 2007}. $h(\cdot)$ is a nonlinear function evaluated numerically from the DP loop following Greene (2003)'s definition for the nonlinear model[23], the derivative of the nonlinear function with respect to the parameter space is assumed to exist. Involving nonlinear structure in the DP system, the MDE (or the nonlinear least squares) is denoted by $\Theta^{l,MDE}$. Then, it is defined as Θ^l such that minimizes the following criterion function

$$G\left(\Theta^l\right) = \frac{1}{2}\sum_{t=2000}^{2007}\left[x_t^{GM,l} - h\left(x_t^{GM,l}, \Theta^l\right)\right] = \frac{1}{2}\sum_{t=2000}^{2007}\varepsilon_t^2. \tag{4.14}$$

The first-order conditions for the minimum $\Theta^{l,MDE}$ are

$$g\left(\Theta^{l,MDE}\right) = -\sum_{t=2000}^{T=2007}\left[x_t^{GM,l} - h\left(x_t^{GM,l}, \Theta^{l,MDE}\right)\right] \cdot \frac{\partial h\left(x_t^{GM,l}, \Theta^{l,MDE}\right)}{\partial \Theta^{l,MDE}} = 0. \tag{4.15}$$

Then, $\Theta^{l,MDE}$ is an estimator that is consistent and asymptotically normal (Greene, 2003, p.167-168). These show how econometric parameter estimation can be incorporated with the DP models. In particular, the asymptotic normality will be useful to implement hypothesis testing on the estimated parameters. It will support the use of a F-test in our empirical testing for the role of risk aversion and individual/social learning in GM adoption, as discussed in the following chapters.

More generally, we can define $\Theta^{l,MDE}$ as follows

[23] A nonlinear regression model is the model, where the first order conditions (F.O.C.) for least squares estimation of the parameters are nonlinear functions of the parameters (Green, 2003, p.165).

$$\Theta^{l,MDE} = \underset{\Theta^{l}}{\arg\min} \sum_{t=2000}^{T=2007} \left[x_t^{GM,l} - x_t^{GM,l}\left(S^l \mid \Theta^l\right) \right]^2 , \tag{4.16}$$

where the nonlinear function $h(\cdot)$ is substituted for the optimal policy function $x_t^{GM,l*}\left(S^l \mid \Theta^l\right)$, which is evaluated at the simulated GM adoption rates $x_t^{GM,l}$ in the DP loop. Also, we define the goodness-of-fit statistic as the sum of squared residuals:

$$d\left(\Theta^l\right) = \sum_{t=2000}^{T=2007} \left[x_t^{GM,l} - x_t^{GM,l}\left(S^l \mid \Theta^l\right) \right]^2 . \tag{4.17}$$

That is, for every DP adoption model, $\Theta^{l,MDE}$ is the parameter vector obtained when the distance between simulated and observed adoption path is minimized or the goodness-of-fit statistic $d\left(\Theta^l\right)$ is minimized.

The parameter space Θ^l is composed of coefficients from the reward function, system equation, and measurement equation in the DP system. They are also part of the Kalman filter algorithm representing state transition equations.[24] The total number of parameters in the parameter space Θ^l amounts to 13, which is too high-dimensional and computationally intractable for estimation purpose (given the "curse of dimensionality" of the DP problem). Consequently, efforts to reduce dimension of Θ^l are considered.

For a lower dimension of Θ^l, cross-technology effects are ignored through the model estimation. First, β_{12}^l is assumed to be zero (see Chapter 3 for the definition of parameters). It means that area-wide suppression of pest population is not addressed in this paper. Second, β_{21}^l is also assumed to be zero as weed control effects through tillage are considered only at the same locations over years. In the context of the aggregate adoption model, it is not possible to identify

[24] For simplicity, this paper focuses on the system and measurement equations rather than the Kalman filter algorithm (which is discussed in Chapter 3).

planted areas for an individual farmer. Third, γ_{12}^{l}, γ_{22}^{l}, and γ_{41}^{l} in the measurement equation (3.24) are assumed to be zero to avoid computational burden; but γ_{31}^{l} is allowed to be non-zero as estimation results deteriorate when γ_{31}^{l} is set equals to zero in the DP model. With those assumptions, the total number of parameters to be estimated reduces to 8, and the parameter space Θ^{l} is

$$\Theta^{l}=\left\{r^{l},\beta_{11}^{l},\beta_{22}^{l},\gamma_{11}^{l},\gamma_{21}^{l},\gamma_{31}^{l},\gamma_{32}^{l},\gamma_{42}^{l}\right\} \tag{4.18}$$

Note that r^{l} in the reward function is the Arrow-Pratt measure of absolute risk-aversion coefficient. Both β_{11}^{l} and β_{22}^{l} are parts of the system equation (3.23), β_{11}^{l} (β_{22}^{l}) being the effect of adoption of conventional (GM) technology on the average change in the next period per-acre net profitability of conventional (GM) seed $\pi_{t+1}^{CONV,l}$ ($\pi_{t+1}^{GM,l}$). All γ^{l} 's are components of the measurement equation (3.24). γ_{11}^{l} (γ_{32}^{l}) is the individual learning parameter for conventional (GM) technology, and γ_{21}^{l} (γ_{42}^{l}) is the social learning parameter for conventional (GM) technology. γ_{31}^{l} is a cross-technology effect reflecting that GM traits are inserted into better conventional seed for higher yield performance.

As mentioned in Section 4.2.1, the dimension of Θ^{l} could be 5 (for the early adopter's model and for the late adopter's model) or 8 (for the aggregate model and for the intermediate adopter's model). To simplify our analysis, we focus our attention on just a few parameters: the parameter measuring risk preferences r^{l} and the parameters capturing individual and social learning, γ_{11}^{l}, γ_{12}^{l}, γ_{32}^{l}, and γ_{42}^{l}. That is, for each farm type $l=\left\{EARLY, INTER, LATE\right\}$, β_{11}^{l} and β_{22}^{l} in the system equation and γ_{31}^{l} in the measurement equation are assumed to be same across different types of disaggregate model as

$$\beta_{11}^{EARLY} = \beta_{11}^{INTER} = \beta_{11}^{LATE}, \tag{4.19}$$

$$\beta_{22}^{EARLY} = \beta_{22}^{INTER} = \beta_{22}^{LATE}, \tag{4.20}$$

$$\gamma_{31}^{EARLY} = \gamma_{31}^{INTER} = \gamma_{31}^{LATE}. \tag{4.21}$$

The above parameters are not necessarily same as parameter estimates in the aggregate adoption model. That is, $\beta_{11}^{l} \neq \beta_{11}$, $\beta_{22}^{l} \neq \beta_{22}$, and $\gamma_{31}^{l} \neq \gamma_{31}$, where parameters without the superscript index l indicate parameters in the aggregate model.

In practice, β_{11}^{l}, β_{22}^{l}, and γ_{31}^{l} are estimated together with other parameters only at the DP model for the intermediate adopter because the intermediate adopter's model is expected to be closer to the aggregate model rather than other extreme DP models such as the early- and the late- adopter's models. In the same way as the aggregate model is estimated, the intermediate adopter's model is estimated on the parameter space Θ^{INTER} composed of 8 parameters in total. The parameters β_{11}^{l}, β_{22}^{l}, and γ_{31}^{l} are then treated as given constants for the other disaggregate models (the early- and the late- adopter's models). Then, the number of parameters in Θ^{EARLY} and in Θ^{LATE} reduces to 5 as β_{11}^{l}, β_{22}^{l}, and γ_{31}^{l} are considered as constants.

This assumption simplifies the computational burden and helps improve empirical tractability. First, lower dimension of Θ^{EARLY} and Θ^{LATE} reduce the computational cost in the DP solution by focusing only on the parameters of risk aversion and individual/social learning. Second, degrees of freedom for the denominator are increased by reducing the number of parameters. This is particularly important given the small number of observations used in our econometric analysis. The increased number of degrees of freedom leads to more reliable hypothesis testing (as further discussed in Chapter 6). Third, with a focus on the effects of risk aversion and individual/social learning on GM adoption, holding irrelevant parameters constant makes it more convenient to evaluate associated parameters across farm types. This will be discussed in more details in Section 6.4.

Chapter 5 : Results and Discussions of the Aggregate GM Technology Adoption Model

This chapter presents the empirical results from the structural dynamic GM adoption model applied at the aggregate model. A model of corn farmer's GM technology adoption is presented. The model involves the estimation of parameters associated with reward function and state transition equations using the Kalman filter algorithm representing learning in Bellman equation. In addition, economic implications of the model are discussed and evaluated. This includes the analyses of selected scenarios with a focus on the rate of GM technology adoption and welfare effects.

The first section reports parameter estimates obtained from the DP model estimation using a minimum distance estimator, along with a discussion of implications for GM technology adoption and learning. The analysis focuses on the role played by risk preferences and individual/social learning. The second section presents selected scenarios evaluating the effects of risk aversion and social learning. For each scenario, hypothesis testing is conducted to examine the statistical significance of the corresponding parameter. The third section does sensitivity analysis on how adoption behavior varies according to changes in each parameter. Finally, the fourth section reports a welfare analysis investigating the effects of risk aversion and social learning on farm welfare. This is done using the farmer's value function from the optimal DP solution obtained in each scenario.

5.1.Parameter Estimates

5.1.1. Parameter Estimates

Using a minimum distance estimator, Table 5.1 reports parameter estimates from the aggregate GM adoption model. The goodness-of-fit of the estimated model is defined as the sum of squared residuals; it is 0.0303 for the aggregate GM adoption model. The goodness-of-fit statistic is used in doing hypothesis testing, as discussed in the following section.

Table 5.1: Parameter Estimates of the Aggregate GM Adoption Model

Parameter	Implication	Estimate
Reward Function		
r	The Arrow-Pratt measure of absolute risk-aversion coefficient	0.54
$\bar{r}$	The Arrow-Pratt measure of relative risk-aversion coefficient	4.12
System Equation		
β_{11}	The effect of adoption of conventional technology on the average change in π^{CONV}	2.20
β_{22}	The effect of adoption of GM technology on the average change in π^{GM}	2.50
Measurement Equation		
γ_{11}	The effect of individual learning for conventional technology	1.21
γ_{21}	The effect of social learning for conventional technology	1.01
γ_{31}	The effect of yield for GM seed to π^{CONV}	1.25
γ_{32}	The effect of individual learning for GM technology	1.80
γ_{42}	The effect of social learning for GM technology	0.80

Note: Goodness of fit is 0.0303.

The only parameter to be estimated in the reward function is r, the Arrow-Pratt measure of absolute risk-aversion coefficient. It is estimated to be 0.54. The sign of r is positive, which reflects that farmers are risk averse. When a new technology is treated as a risky asset, this risk exposure affects technology adoption as discussed in previous studies (Besley and Case, 1994; Baerenklau, 2005). The Arrow-Pratt measure of relative risk aversion coefficient $\bar{r}$ is reported together with r. $\bar{r}$ provides a more convenient measure of risk aversion than r. Indeed, while r depends on the units of monetary measurements, $\bar{r}$ is a unit-free measurement as it measures the elasticity of the marginal utility of income (Chavas, 2004). $\bar{r}$ is obtained by multiplying expected profit by r. At the aggregate model, a representative farmer's expected profit is estimated as \$7.63 million from planting both conventional and GM seeds.[25] Then, $\bar{r}$ is estimated as 4.12, which indicates that his/her risk aversion seems to be in the medium range as $1 \le \bar{r} \le 5$.[26]

Estimated parameters in the system equation β_{11} and β_{22} are all positive, indicating that the adoptions of both conventional technology and GM technology improve profitability for each technology. The effect of GM technology adoption on the profitability of GM β_{22} is found to be greater than that of conventional technology β_{11}. Thus, farmers see GM technology as more profitable on average compared to conventional technology. However, the difference between β_{11} and β_{22} is not large. This can help explain why the adoption of GM technology is slow.

Note that the γ's in the measurement equation reflect the degree of correlation between observed signals and the unobservable states. Non-negative γ's indicate a positive correlation between observations in the measurement equation and unobservable state variables. γ_{11} or γ_{32} being zero would imply that farmers don't learn anything from their own experience in adopting any technology. And γ_{21} or γ_{42} being zero would imply that farmers don't learn from their

[25] As described in Chapter 4, throughout this paper, a representative farmer is understood to represent the whole famers only in terms of adoption rates not farm size; sub-sample farmers of the DMR panel data are considerably large farmers as their average total profit \$7.63 million is very large compared with USDA-ERS sources (Ifft and Morehar, 2012).

[26] The level of risk aversion is classified as 'very low' ($\bar{r} < 1$), 'medium' ($1 \le \bar{r} \le 5$), and 'very high' ($\bar{r} > 5$) (Gollier, 2001, p. 31).

neighbors (no social learning). Thus, if there exist effects of individual and social learning, γ's would be positive values. According to Table 5.1, all parameter estimates for γ's are positive, which means that both individual learning and social learning influence the profitability for each technology in positive directions. In addition, γ_{31} is positive, indicating a positive relationship between the yield of GM seeds and the performance of conventional seeds.

The relative role of individual vs. social learning is analyzed by comparing degrees of γ_{11} and γ_{21} for conventional technology and degrees of γ_{32} and γ_{42} for GM technology. For conventional technology, the individual learning parameter γ_{11} is greater than the social learning parameter γ_{21}. Similarly for GM technology, the individual learning parameter γ_{32} is greater than the social learning parameter γ_{42}. This finding is consistent with the empirical results obtained by Munshi (2004), Baerenklau (2005), and Conley and Udry (2010); they show that new technology is adopted more effectively through self-experiment (individual learning) than neighborhood effects (social learning).

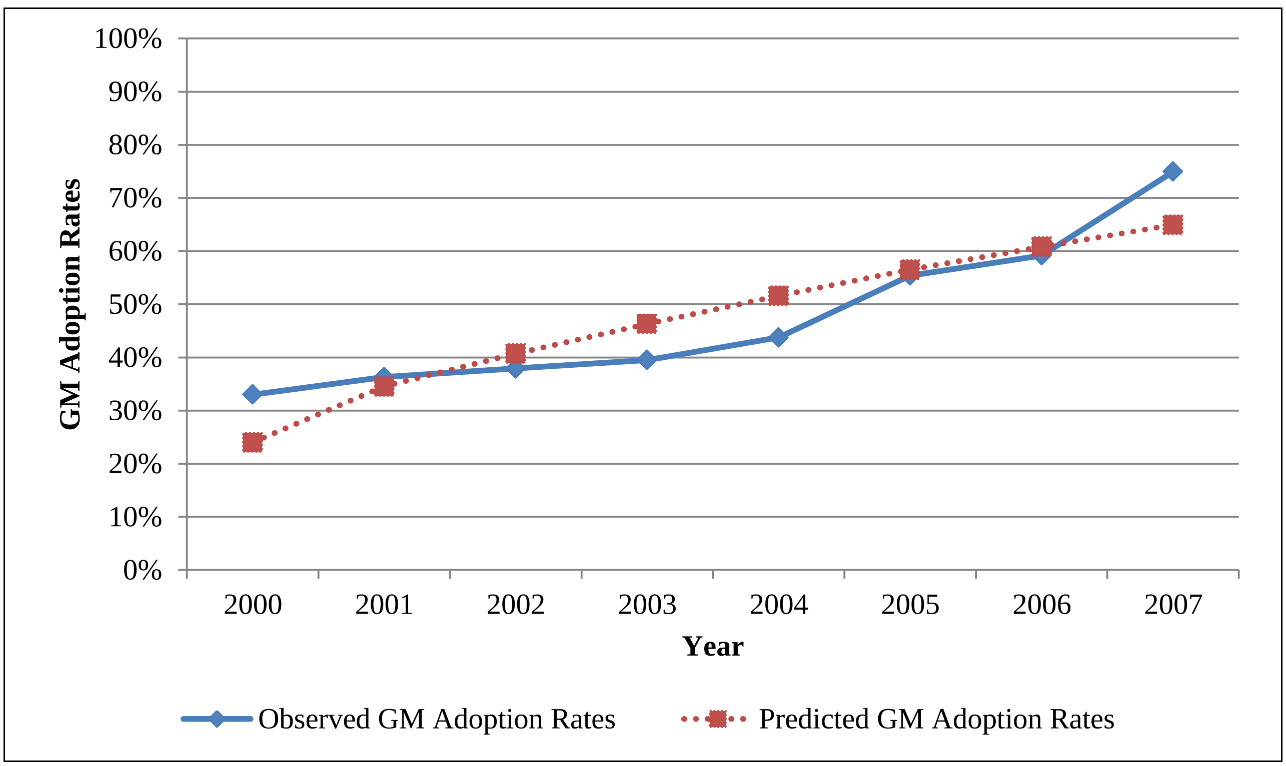
Note that the social learning parameter is higher for conventional seeds (γ_{21}) than for GM seeds (γ_{42}). This indicates that farmers acquire relatively more knowledge about the profitability from their neighbors (social learning) for conventional technology than for GM technology. This is intuitive to the extent that conventional seeds are not new, reflecting the short history of new technology (GM varieties) and the presence of fewer neighbors who already adopted GM technology in the early introduction period. Importantly, γ_{21} and γ_{42} being both positive indicate the presence of social learning.

As further discussed below, social learning for GM technology involves an information externality. If a farmer waits for his/her neighbors to adopt GM technology so that he/she can learn from neighbors, this will provide an incentive to delay adoption. This issue will be evaluated in more details in Section 5.3.

5.1.2. Adoption Curve

Based on the parameter estimates reported in the previous section, the predicted adoption rates of GM technology are obtained from the DP model. These predicted values are compared with actual adoption rates in Figure 5.1.

Figure 5.1: Observed and Predicted GM Adoption Rates at the Aggregate Model, 2000-2007



Note: GM adoption rates are percentage of planted acres to GM seed.

The observed GM adoption rates are drawn from the DMR panel data set. The aggregate adoption curve represents the average adoption rates of 136 farmers in and around the U.S. Corn

Belt from 2000 through 2007. The shape of the observed path is similar to a typical logistic adoption curve. However, the aggregate adoption curve doesn't reflect the early phase as the analysis period of this paper starts in 2000 while GM corn was commercially introduced in 1996.

The predicted GM adoption rates are generated by doing Monte Carlo simulation 10,000 times over an 8-year period from 2000 through 2007 after solving the infinite time horizon DP problem for the aggregate GM adoption model with estimated parameters given in Table 5.1. Table 5.2 presents the predicted and observed GM adoption rates in Figure 5.1 with terms of squared residuals. As described in Section 5.1.1, the goodness-of-fit of the estimated model is 0.0303; the aggregate GM adoption model has a good predicted power. Overall, the estimated model fits data fairly well throughout the analysis period, although it underestimates observed GM adoption rates by 9% in 2000 and by 10% in 2007.

Table 5.2: Observed and Predicted GM Adoption Rates at the Aggregate Model, 2000-2007

Year	Observed GM Adoption Rates[a/]	Predicted GM Adoption Rates[b/]	Squared Residual[c/]
2000	33.01%	24.03%	0.0081
2001	36.30%	34.53%	0.0003
2002	37.90%	40.73%	0.0008
2003	39.52%	46.28%	0.0046
2004	43.74%	51.57%	0.0061
2005	55.40%	56.51%	0.0001
2006	59.18%	60.80%	0.0003
2007	74.96%	64.92%	0.0101
Sum of Squared Residuals (Goodness-of-fit statistic)			0.0303

Note: [a/] [b/] GM adoption rates are percentage of planted acres to GM seed.
[c/] Squared residual c/ = $(a/ - b/)^2$

Discrepancies between observed and predicted rates can come from several sources. First, the aggregate model applies to a representative farm and doesn't capture farm level heterogeneity. Second, the analysis considers a simplified choice problem between conventional and GM technology. It ignores issues of adoption of multiple GM traits. While HT and IR-ECB traits were introduced in the mid 1990's during the earlier phase of GM technology innovation, the adoption of IR-RW trait and stacked seeds started in the later phase and accelerated the speed of diffusion in the late 2000's. Issues related to farm level heterogeneity will be evaluated in Chapter 6.

5.2.Hypothesis Testing

5.2.1. Hypothetical Scenarios

Section 5.1 discussed the economic implications of parameter estimates. This section evaluates the statistical significance of parameter estimates from an econometric viewpoint. This involves hypothesis testing for selected parameters. This is done by simulating the DP model for the aggregate GM adoption under alternative hypotheses.

Hypothesis testing focuses on farm risk preferences r in the reward function and on the parameters γ's associated with learning in the measurement equation. This provides an econometric basis to analyze the impacts of risk aversion and individual vs. social learning on technology adoption. Table 5.3 presents the null hypotheses investigated in this Chapter.

The null hypothesis in Scenario 1 involves a counterfactual case where a farmer's risk preferences exhibit risk neutrality. Scenario 2 and Scenario 3 bring in situations where social learning doesn't play any role in adopting conventional and GM technology, respectively. Further, Scenario 4 considers the case where the farmer learns about profitability of both conventional and GM technology using only his/her own experience (i.e., without any social interaction). In addition, Scenario 5 and Scenario 6 investigate whether the social learning parameter is the same across technologies (1.01 for Scenario 5 and 0.80 for Scenario 6).

Table 5.3: Null Hypotheses for Hypothetical Scenarios at the Aggregate Model

Scenario *sc*	Null Hypothesis	Implication
1	$H_0 : r = 0$	Risk neutral vs. risk aversion
2	$H_0 : \gamma_{21} = 0$	No social learning for non-GM technology adoption only
3	$H_0 : \gamma_{42} = 0$	No social learning for GM technology adoption only
4	$H_0 : \gamma_{21} = 0 \,\&\, \gamma_{42} = 0$	No social learning both for non-GM and for GM technologies
5	$H_0 : \gamma_{21} = \gamma_{42} = 1.01$	Size comparison of the degree of social learning across technologies at the level of non-GM technology
6	$H_0 : \gamma_{21} = \gamma_{42} = 0.80$	Size comparison of the degree of social learning across technologies at the level of GM technology

These scenarios are used to conduct hypothesis testing. For each scenario, marginal impacts of zero vs. non-zero parameter on goodness-of-fit are evaluated. In this context, Scenario 1 and Scenario 3 provide useful information on the role of risk preference and of social learning in GM technology adoption.

5.2.2. Hypothesis Testing across Scenarios

Note that the model is nonlinear (due to the nonlinear structure of the Kalman filter algorithm). Thus, hypothesis testing relies on a testing procedure applied to nonlinear regression models. It can include the Wald, the likelihood ratio, and the Langrage multiplier test statistics. In the nonlinear case, the Wald statistic is asymptotically equivalent to the F statistic times the number of restrictions denoted as $N_{restrictions}$. In case of small sample, the F-test is preferred to the Wald test (Greene, 2003). As the GM adoption curve is simulated over only 8 years, the sample size for this paper is small, and the F-test appears more appropriate to do the hypothesis testing reported in this paper.

Though the F-test is helpful in dealing with the small sample size, there still exist obstacles to do hypothesis testing. Clearly, the number of degrees of freedom must be positive. Given $N_{observations} = 8$, this limits our hypothesis testing to consider just a few parameters. Our analysis focuses on parameters for risk preference and individual vs. social learning. This involves $N_{parameters}$ = 6.

Θ indicates the parameter space of the unrestricted nonlinear minimum distance estimator, being considered as the baseline parameter space in Table 5.1. Indexing sc as a selected scenario in Table 5.3, Θ_*^{sc} indicates the parameter space of the estimator under the null hypothesis of scenario sc. For each sc = {Scenario 1, Scenario 2, …, Scenario 6}, the F-statistic is defined as

$$F^{sc}\left(N_{restrictions}^{sc}, N_{observations} - N_{parameters}\right) = \frac{\left\{\dfrac{SSR\left(\Theta_*^{sc}\right) - SSR(\Theta)}{N_{restrictions}^{sc}}\right\}}{\left\{\dfrac{SSR(\Theta)}{\left(N_{observations} - N_{parameters}\right)}\right\}}, \tag{5.2}$$

where $SSR(\Theta)$ and $SSR\left(\Theta_*^{sc}\right)$ are the sum of squared residuals (goodness-of-fit statistic) under Θ and Θ_*^{sc}, respectively. Under each scenario sc in Section 5.2.1, the DP model for the aggregate GM adoption is simulated under Θ and Θ_*^{sc}. Then, the goodness-of-fit statistics $SSR(\Theta)$ and $SSR\left(\Theta_*^{sc}\right)$ are calculated and used for evaluating the F-test statistic in (5.2). This provides a basis for a statistical test of selected hypotheses.

For example, under Scenario 1, the null hypothesis is $H_0: r = 0$, testing whether farm risk preferences exhibit risk aversion versus risk neutrality. Then, Θ is composed of r = 0.54 and other parameter estimates given in Table 5.1, but $\Theta_*^{sc=\{Scenario1\}}$ has r = 0 holding other parameters constant at their estimated values in Table 5.1. The sum of squared residuals between observed data and simulated rates (goodness-of-fit statistic) is calculated as $SSR(\Theta)$ = 0.0303 given Θ and $SSR\left(\Theta_*^{sc=\{Scenario1\}}\right)$ = 1.7816 given $\Theta_*^{sc=\{Scenario1\}}$. Using (5.2) with $N_{restrictions}^{sc=\{Scenario1\}}$ = 1, $N_{observations}$ = 8, and $N_{parameters}$ = 6, the F-static is calculated as $F^{sc=\{Scenario1\}}(1,2)$ = 115.43, being larger than 98.80, the critical value of the 99th percentiles of the F-distribution with (1, 2) degrees of freedom under the null hypothesis. Thus, the null hypothesis $H_0: r = 0$ is rejected at the 1% significance level, implying farm risk preferences exhibit risk aversion. Therefore, this testing result strongly supports that farmers are risk averse and that their risk preferences affect GM technology adoption. Table 5.4 presents results of hypothesis testing for each scenario.

Table 5.4: Results of Hypothesis Testing across Scenarios at the Aggregate Model

Scenario *sc*	Null Hypothesis	SSR(Θ)[a/]	SSR(Θ_*^{sc})[b/]	df1[c/]	df2[d/]	F ^{SC} (df1, df2)[e/]
1	$H_0: r = 0$	0.0303	1.7816	1	2	115.43***
2	$H_0: \gamma_{21} = 0$	0.0303	0.0621	1	2	2.09
3	$H_0: \gamma_{42} = 0$	0.0303	1.5191	1	2	98.13**
4	$H_0: \gamma_{21} = 0 \& \gamma_{42} = 0$	0.0303	1.9509	2	2	63.29**
5	$H_0: \gamma_{21} = \gamma_{42} = 1.01$	0.0303	0.3416	2	2	10.26*
6	$H_0: \gamma_{21} = \gamma_{42} = 0.80$	0.0303	1.4665	2	2	47.33**

Note Statistical significance is denoted as *** at the 1% level, ** at the 5% level, and * at the 10% level.
[a/] Goodness-of-fit statistic under Θ
[b/] Goodness-of-fit statistic under Θ_*^{sc}
[c/] Degrees of freedom for the numerator
[d/] Degrees of freedom for the denominator
[e/] F-statistic

Null hypotheses are rejected at the 1% significance level for Scenario 1, at the 5% significance level for Scenario 3, Scenario 4, and Scenario 6, and at the 10% significance level for Scenario 5. Especially, the F-statistics under Scenario 1 and Scenario 3 are shown to be the highest and the second highest across scenarios. Those results mean that the impacts of risk aversion and social interaction on GM technology adoption are highly significant. Note that the null hypothesis is not rejected for Scenario 2.

The effect of social interaction is shown to be somehow different according to the technology. For non-GM technology, we fail to reject the null hypothesis of $H_0 : \gamma_{21} = 0$, which means the impact of social learning for non-GM technology is not statistically significant in accounting for farmers' GM technology adoption behavior. On the contrary, for GM technology, null hypotheses of no social learning under Scenario 3 and Scenario 4 are strongly rejected at the 5% significance level. Especially, the F-statistic for Scenario 4, 98.13 is marginally close to the critical value of the 99th percentiles of the F distribution with F(1,2), 98.50. So, the null hypothesis of Scenario 4 can be rejected almost at the 1% significance level. This provides evidence that social interaction plays a key role in GM technology adoption.

Finally, null hypotheses of similar impacts of social interaction between non-GM and GM technology are rejected as shown in Scenario 5 and Scenario 6. Those test results show that the magnitudes of social learning effects are different across technologies.[27] As presented in Table 5.1, social interaction for non-GM technology γ_{21} = 1.01 is larger than that for GM technology γ_{42} = 0.80. As discussed in Section 5.1.1, the case of $\gamma_{21} > \gamma_{42}$ may be explained by the difference in history for each technology; farmers learn about the profitability of

[27] The marginal impact by changes in γ_{42} is discussed in the following section in terms of sensitivity analysis.

conventional seed more from neighbors as the old technology (conventional seed) has a longer history compared to the new GM technology which has a shorter history.

5.3. Sensitivity Analysis

Hypothesis testing in the previous section provides useful econometric evidence on the role of selected parameters affecting GM technology adoption. This section expands the evaluation of the results by conducting sensitivity analysis. Specifically, this section explores how the aggregate GM adoption curve varies as selected parameters change. The emphasis is on analyzing impacts of risk aversion and social learning on GM technology adoption.

5.3.1. Sensitivity Analysis of Risk Aversion

The Arrow-Pratt coefficient of absolute risk-aversion r can be expected to affect the speed of GM technology adoption. To document the nature and magnitude of this effect, the DP model of the aggregate GM adoption is simulated at different levels of r holding other parameters constant at their estimated value. Figure 5.2 illustrates selected simulations of GM technology adoption over 8 years, with r starting from the minimum distance estimates 0.54 to a considerably high level $r = 3.51$. Specific values are provided in Table 5.5.

The estimated GM adoption with $r = 0.54$ is used as a benchmark curve represented as a dashed line in Figure 5.2. Movements of GM adoption curves are not monotonic in terms of risk aversion; simulated GM adoption curves move upward ranging from $r = 0.54$ to $r = 2.16$, whereas they move downward beyond $r = 2.16$ up to $r = 3.51$.

Figure 5.2: Simulation of the GM Technology Adoption by Changes in Risk Aversion at the Aggregate Model

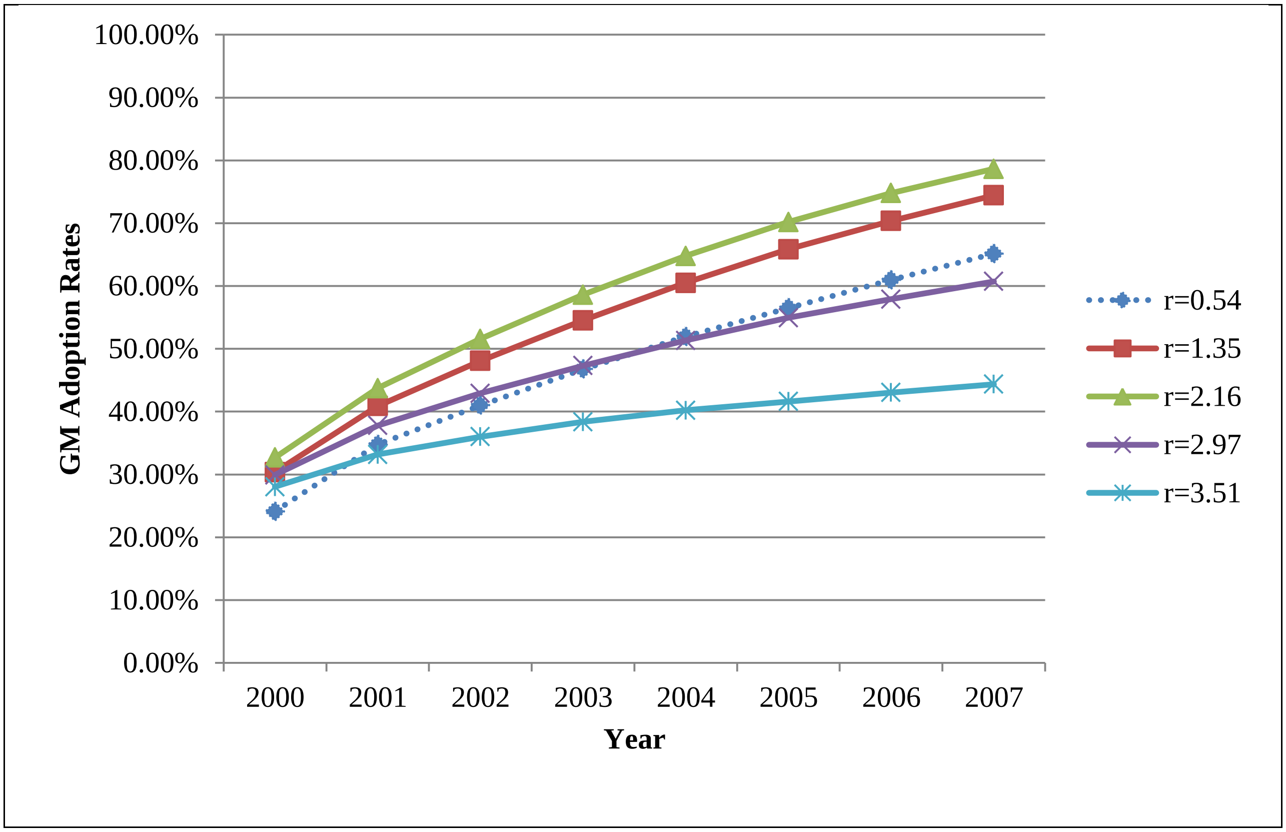
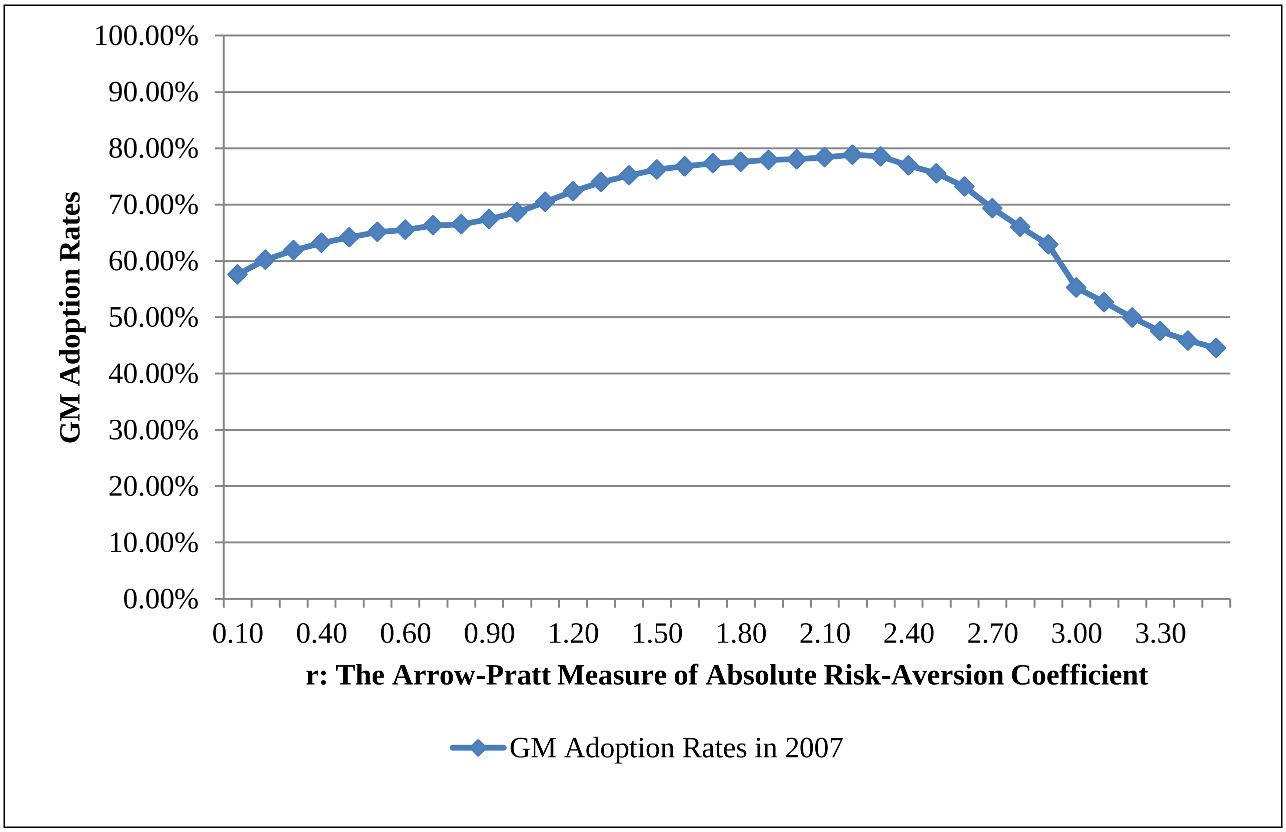


Table 5.5: Simulations of GM Technology Adoption by Changes in Risk Aversion at the Aggregate Model

Risk Aversion	Simulated GM Adoption Rates at the Aggregate Model								Goodness-of-fit
r	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	
0.54	24.10%	34.76%	41.00%	46.76%	51.93%	56.51%	60.96%	65.13%	0.03
1.35	30.37%	40.90%	48.09%	54.54%	60.51%	65.86%	70.37%	74.45%	0.09
2.16	32.69%	43.73%	51.57%	58.61%	64.78%	70.19%	74.81%	78.65%	0.15
2.97	29.91%	37.80%	42.91%	47.32%	51.34%	54.94%	57.91%	60.74%	0.04
3.51	28.03%	33.17%	36.02%	38.39%	40.22%	41.62%	43.03%	44.36%	0.14

To evaluate this non-monotonicity, simulated adoption rates in a fixed time period 2007 are drawn in Figure 5.3 with r ranging from 0.10 to 3.50 and segmented by 0.10. Simulated adoption rate in 2007 increases gradually from 57.60% at the starting point $r = 0.10$ and reaches a peak of 78.82% at $r = 2.20$. However, it falls from its peak as r increases over 2.20 and declines rapidly to 44.54% at $r = 3.50$.

Figure 5.3: Simulated GM Adoption Rates in 2007 by Changes in Risk Aversion at the Aggregate Model



Simulation results show that increments in risk aversion accelerate the speed of GM technology adoption up to a certain level of r ($r < 2.20$) but decelerates the adoption speed at a higher level of r ($r > 2.20$). Such a non-monotonic effect can be explained as follows: first, at a relatively higher level of $r > 2.20$, risk-averse farmers delay GM technology adoption as they see the new technology as a risky asset (Besley and Case, 1994; Baerenklau, 2005). In this case, the more risk-averse farmers are, the later they adopt a new technology (e.g., Liu, 2008). Second, a different impact of risk aversion on GM adoption can arise in the context of farmers' portfolio selection. As discussed in Chapter 3, this paper assumes that both GM technology and conventional technology are risky, with uncertain profitability and learning for both. That assumption is distinctive from Besley and Case (1994) and Baerenklau (2005), where an old technology is considered to be risk-free. In the case where both technologies are risky, farmers may want to diversify their adoption choices.

Under expected utility maximization, diversification can help lower risk (variance). A mixture of two risky technologies can reduce risk exposure when the correlation coefficient between conventional and GM profitability $\rho_{CONV,GM}$ is small or negative (Anderson et al., 1977). In the model, $\rho_{CONV,GM}$ is calculated as 0.2948 on average, which may be small enough to provide a risk averse farmer with an incentive to diversify. In this case, the diversification motive can possibly speed up the adoption of GM technology. This occurs in our simulations for r < 2.20.[28]

In sum, the impact of risk aversion on GM technology adoption is non-monotonic. Increment in risk aversion enhances the speed of GM technology adoption for $r < 2.20$ due to farmers' portfolio selection but slows down the adoption speed as the level of risk aversion is high, $r > 2.20$.

5.3.2. Sensitivity Analysis of Social Learning for GM Technology Adoption

The impact of the social interaction parameter for GM technology γ_{42} is investigated through sensitivity analysis. Similar to the procedure in Section 5.3.1, the DP model is simulated at

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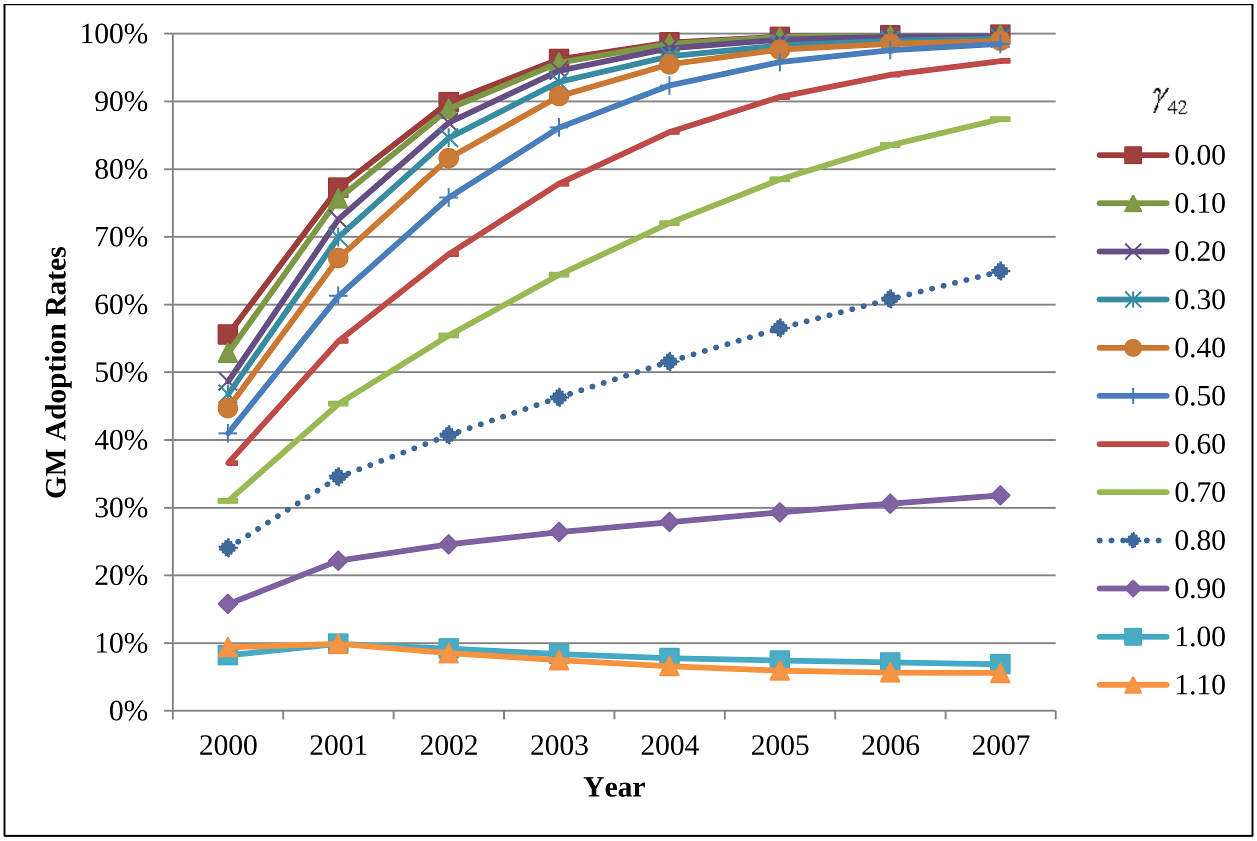
[28] In solving the DP model, the correlation coefficient in 2000 $\rho_{CONV,GM}$ = 0.3363 is used for composing a variance-covariance matrix in the Kalman filter algorithm.

increasing levels of γ_{42} holding other parameters constant at their estimated value. Figure 5.4 and Table 5.6 present changes in simulated GM technology adoption curves according to increases in γ_{42}.

Figure 5.4: Simulation of the GM Technology Adoption by Changes in the Social Learning Parameter at the Aggregate Model



The dashed line indicates the benchmark GM adoption curve when goodness-of-fit is best. Ranging from $\gamma_{42} = 0$ to $\gamma_{42} = 1.10$, the simulated GM adoption curves at the aggregate model show a steady downward movement as γ_{42} increases. Unlike the case of risk aversion, the impact of social interaction on the adoption speed is monotonic: social learning provides an incentive to delay GM adoption.

Table 5.6: Simulation of the GM Technology Adoption by Changes in the Social Learning Parameter at the Aggregate Model

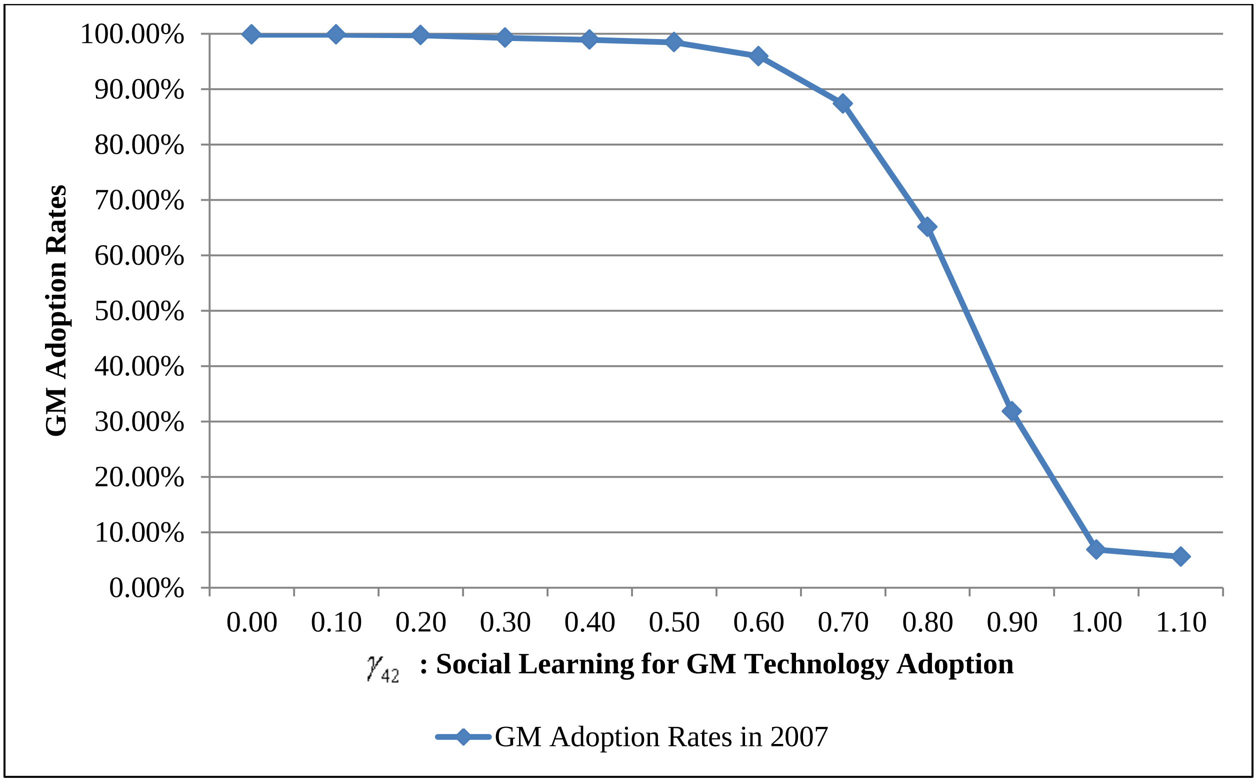
Social Learning	Simulated GM Adoption Rates at the Aggregate Model								Goodness-of-fit
γ_{42}	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	
0.00	55.57%	77.25%	89.90%	96.26%	98.71%	99.54%	99.78%	99.86%	1.53
0.10	52.86%	75.63%	88.91%	95.72%	98.50%	99.48%	99.77%	99.87%	1.49
0.20	48.66%	72.59%	86.88%	94.55%	97.85%	99.11%	99.57%	99.74%	1.41
0.30	46.77%	69.96%	84.63%	92.87%	96.69%	98.28%	99.00%	99.28%	1.32
0.40	44.72%	66.85%	81.62%	90.77%	95.47%	97.63%	98.53%	98.95%	1.22
0.50	40.97%	61.28%	75.81%	86.13%	92.36%	95.80%	97.57%	98.49%	1.03
0.60	36.57%	54.60%	67.45%	77.85%	85.48%	90.65%	93.94%	95.96%	0.73
0.70	30.97%	45.35%	55.44%	64.40%	72.04%	78.48%	83.53%	87.39%	0.31
0.80	24.03%	34.53%	40.73%	46.28%	51.57%	56.51%	60.80%	64.92%	0.03
0.90	15.76%	22.18%	24.58%	26.40%	27.87%	29.30%	30.58%	31.82%	0.45
1.00	8.21%	9.90%	9.20%	8.38%	7.77%	7.43%	7.14%	6.88%	1.40
1.10	9.39%	9.88%	8.50%	7.48%	6.58%	5.93%	5.65%	5.58%	1.47

Starting from the extreme case of no social interaction ($\gamma_{42} = 0$), simulated GM adoption rate curves keep decreasing as γ_{42} increases by 0.10 up to $\gamma_{42} = 1.10$. Fixing a time period at a particular year 2007, the trend of simulated GM adoption rates due to changes in γ_{42} is illustrated in Figure 5.5.

For instance, a simulated GM adoption rate in 2007 falls to 5.58% for $\gamma_{42} = 1.10$ (compared to a full adoption of 99.87% for $\gamma_{42} = 0.10$). In addition, adoption of GM technology is slower as γ_{42} increases. Define the saturation time point as the year GM technology is almost fully adopted with percentage of over 95%. In the absence of social interaction, GM adoption rate would reach 96.26% very early during the analysis period, the saturation time point being

2003. However, the saturation time point moves downward to 2004 for $\gamma_{42} = 0.40$, 2005 for $\gamma_{42} = 0.50$, and 2007 for $\gamma_{42} = 0.60$.

Figure 5.5: Simulated GM Adoption Rates in 2007 by Changes in the Social Learning Parameter at the Aggregate Model



From those empirical results, we find that more intensive social interactions for GM technology slow down the speed of GM adoption at the aggregate model. This reflects the presence of information externality, where acquisition of information from neighbors impedes one's GM technology adoption.[29] This situation occurs when farmers take wait-and-see attitudes until they find what their neighbors are actually doing in adopting GM technology. As a result,

[29] From the viewpoints of adoption rates, social learning is interpreted as 'negative information externality.'

there is an incentive to delay GM adoption through social interaction under information externality.

5.4.Welfare Analysis

This section analyzes the welfare effects associated with risk aversion and social learning of corn farmers. Both cost of risk and cost of social learning are calculated by comparing welfare measures at different levels of selected parameters.

In a way similar to the previous section, welfare analysis is done by investigating the impacts of parameters r and γ_{42} on welfare measure. The certainty equivalent is used for measuring welfare (Chavas, 2004). The reward function in the DP model in Chapter 3 is represented by an additive mean-variance function, which is a certainty equivalent itself with its variance component interpreted as a measure of the risk premium. In dynamic models, the value function of the Bellman equation gives the present value of all future risk-adjusted benefits. Thus, the value function is interpreted as a certainty equivalent measure and is used in a welfare indicator.

This section focuses on analyzing value functions in the DP simulations under alternative hypothetical situations. The first sub-section investigates value functions at different levels of risk aversion r and evaluates the associated cost of risk. The second sub-section goes through a similar exercise to evaluate the welfare effects of social learning.

5.4.1. Welfare Analysis of Risk Aversion

The parameter estimates space using a minimum distance estimator is expressed as Θ^{MDE}, and the state space is denoted as S, where S is composed of sufficient statistics – mean and variance of the proftability for conventional and GM technology, $S=\left\{\mu^{CONV},\sigma^2_{CONV},\mu^{GM},\sigma^2_{GM}\right\}$. The optimal value function given a state space under the minimum distance estimator is represented as $V\left(S\,|\,\Theta^{MDE}\right)$. This section considers the effects of selected parameters on the value function $V\left(S\,|\,\Theta\right)$. This involves evaluating $V\left(S\,|\,\Theta\right)$ at every possible combination on the state space. But the dimension of the state space is very high: the total number of combinations is 15^4 = 50,625 in the DP model.[30] To simplify the discussion, this section considers the optimal value function evaluated at points as close as possible to average values in the staring year 2000, S = {3.57, 0.06, 3.57, 0.11}.[31]

Referring to Scenario 1 in Section 5.2.2, the value function under risk-neutrality $V\left(S\,|\,\Theta^{r=0}\right)$ can be understood as a welfare measure reflecting only the mean effect (since the variance-covariance term is eliminated from the model under risk neutrality when r = 0). On the contrary, the baseline value function $V\left(S\,|\,\Theta^{r=0.54}\right)$ or $V\left(S\,|\,\Theta^{MDE}\right)$ corresponds to a welfare measure considering both mean- and variance- effects under risk aversion. Then, the difference between $V\left(S\,|\,\Theta^{r=0}\right)$ and $V\left(S\,|\,\Theta^{r=0.54}\right)$ can be interpreted as measuring the (absolute) cost of risk under risk aversion. Thus, the absolute cost of risk aversion is defined as

$$C_{risk-aversion}=V\left(S\,|\,\Theta^{r=0}\right)-V\left(S\,|\,\Theta^{r}\right), \tag{5.3}$$

---

[30] We discretized each state variable (mean and variance for each technology) with 15 evaluation points between given lower bounds and upper bounds.

[31] The expected values in 2000 are 3.56 for μ^{CONV}, 0.09 for σ^2_{CONV}, 3.64 for μ^{GM}, and 0.12 for σ^2_{GM}.

where $C_{risk-aversion} \geq 0$. $C_{risk-aversion}$ is the amount a farmer is willing to pay in order to eliminate risk (variance). Define $\bar{C}_{risk-aversion}$ as the relative cost of risk aversion, obtained by dividing the absolute cost of risk aversion $C_{risk-aversion}$ by the optimal value function given r:

$$\bar{C}_{risk-aversion} = \frac{V\left(S \mid \Theta^{r=0}\right) - V\left(S \mid \Theta^{r}\right)}{V\left(S \mid \Theta^{r}\right)} \times 100, \tag{5.4}$$

where $\bar{C}_{risk-aversion} \geq 0$. Note that $\bar{C}_{risk-aversion}$ is a percentage and is independent of the units of monetary measurements.

At the given evaluation points, $\bar{C}_{risk-aversion}$ between $V\left(S \mid \Theta^{r=0}\right)$ and $V\left(S \mid \Theta^{r=0.54}\right)$ is 3.90%, which is positive and corresponds to the relative cost of risk aversion. It means that a risk-averse farmer would pay 3.90% of the value function to eliminate all risk faced in the baseline case. In short, under production risk (involving both conventional and GM technology), the farmer is worse off compared to the counterfactual case of risk-neutrality. This is consistent with risk aversion.

The next concern is to experiment how farm welfare changes with risk aversion. Figure 5.6 illustrates the changes of the optimal value functions at different levels of risk aversion. Starting from the risk neutral case, the optimal value functions are obtained from the DP simulations with risk aversion ranging from r = 0 to r = 3.50. According to Figure 5.6, welfare measures decline monotonically as the level of risk aversion increases. Table 5.7 provides associated variables with the relative cost of risk aversion.

Figure 5.6: Welfare Measures for GM Technology Adoption by Changes in Risk Aversion at the Aggregate Model

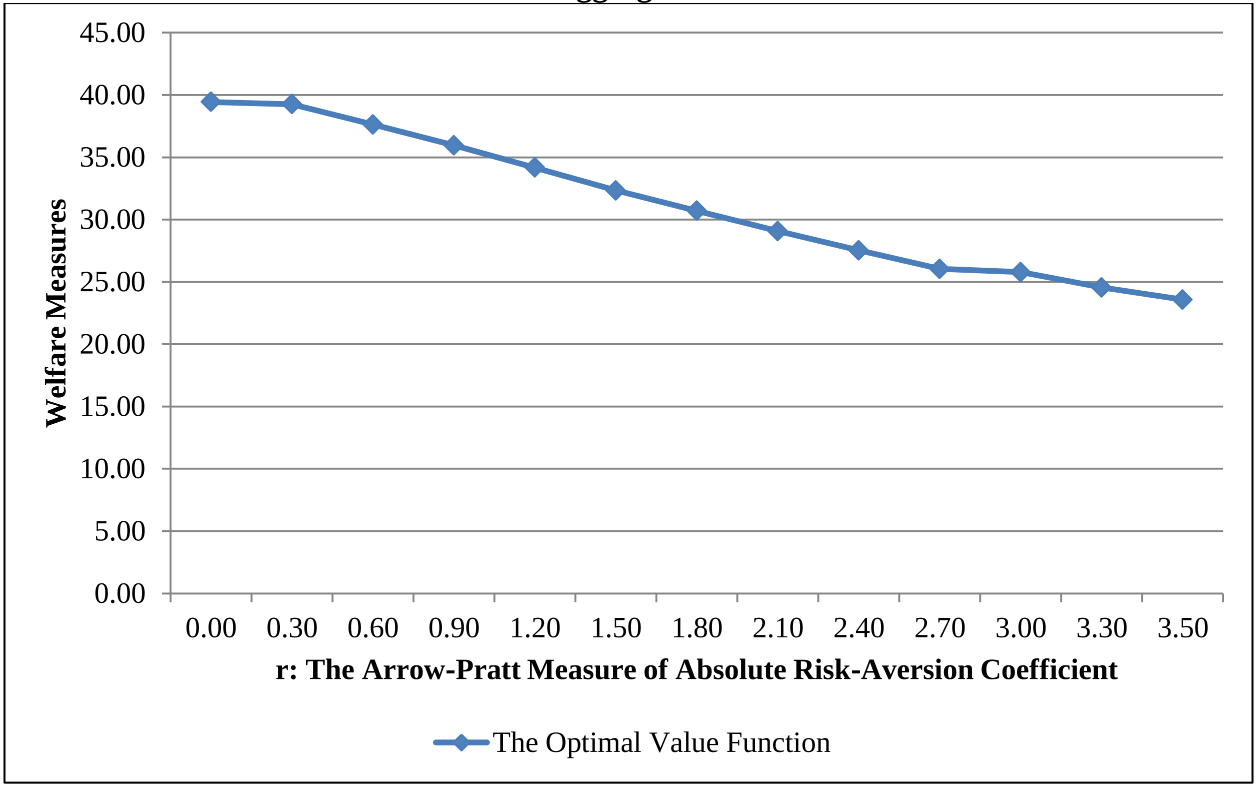


Table 5.7: Welfare Measures and Costs of Risk Aversion at the Aggregate Model

Risk Aversion (Absolute)	The Optimal Value Function[a/]	Absolute Cost of Risk Aversion[b/]	Relative Cost of Risk Aversion (percent)
r	$V\left(S \mid \Theta^r\right)$	$C_{risk-aversion}$	$\bar{C}_{risk-aversion}$
0.00	39.44	0.00	0.00%
0.30	39.26	0.18	0.45%
0.54[c/]	37.96[c/]	1.48[c/]	3.90%[c/]
0.60	37.63	1.81	4.80%
0.90	35.97	3.47	9.66%
1.20	34.17	5.27	15.42%
1.50	32.33	7.11	21.98%
1.80	30.70	8.74	28.46%
2.10	29.08	10.36	35.64%
2.40	27.53	11.91	43.28%
2.70	26.05	13.39	51.43%
3.00	25.78	13.66	52.97%
3.30	24.54	14.90	60.69%
3.50	23.57	15.87	67.33%

Note: [a/ b/] Unit - $ hundred / acre
[c/] The baseline case at the minimum distance estimator

The relative cost of risk aversion $\bar{C}_{risk-premium}$ increases with the level of risk aversion, ranging from 0% to 67.33%. For example, if farm risk aversion is very high with r = 2.40, a risk averse farmer would pay 43.28% of the value function to eliminate risk. That is, he/she has to pay much more in bearing his/her risk rather than just 3.90% of the value function in the baseline case. That is, highly risk-averse farmers would pay more to eliminate their risk exposure. As expected, under production risk, farmers are made worse off when they become more risk averse.

5.4.2. Welfare Analysis of Social Learning for GM Technology Adoption

Following the discussion presented in Section 5.4.1, the optimal value function in terms of social interaction γ_{42} is denoted as $V\left(S \mid \Theta^{\gamma_{42}}\right)$. Given the social learning parameter γ_{42}, γ_{42}^* is termed as "socially optimal" when γ_{42}^* is such that it maximizes $V\left(S \mid \Theta^{\gamma_{42}}\right)$. That is, social optimum γ_{42}^* is defined as

$$\gamma_{42}^* \equiv \arg\max_{\gamma_{42}} \left\{V\left(S \mid \Theta^{\gamma_{42}}\right)\right\}. \tag{5.5}$$

Then, the difference between $V\left(S \mid \Theta^{\gamma_{42}^*}\right)$ and $V\left(S \mid \Theta^{\gamma_{42}}\right)$ given γ_{42} is defined as the (absolute) cost of social learning, denoted as $C_{social-learning}$:

$$C_{social-learning} = V\left(S \mid \Theta^{\gamma_{42}^*}\right) - V\left(S \mid \Theta^{\gamma_{42}}\right). \tag{5.6}$$

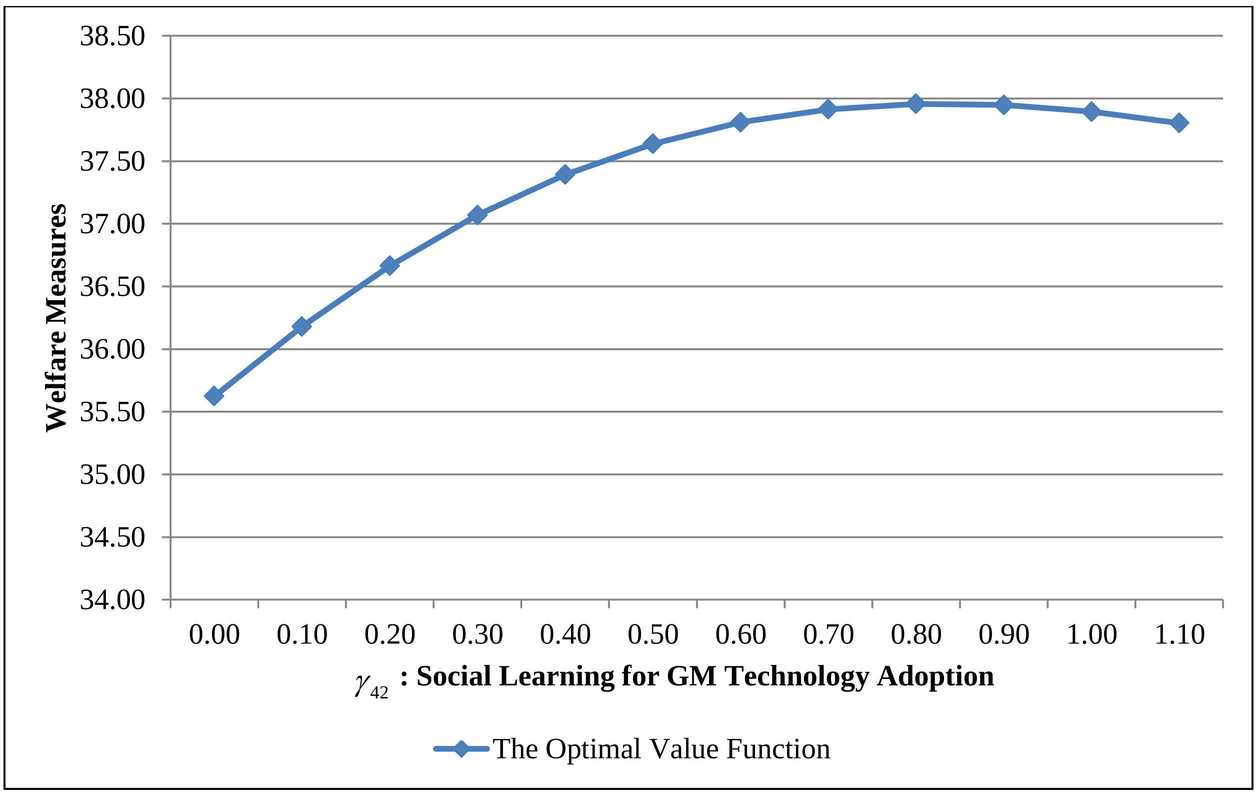
$C_{social-learning}$ reflects the farmer's cost associated with social learning. Alternatively, define the relative cost of social learning as

$$\bar{C}_{social-learning} = \frac{V\left(S \mid \Theta^{\gamma_{42}^{*}}\right) - V\left(S \mid \Theta^{\gamma_{42}}\right)}{V\left(S \mid \Theta^{\gamma_{42}}\right)} \times 100 \qquad (5.7)$$

That is, $\bar{C}_{social-learning}$ represents the percentage change in the value function associated with social learning.

Figure 5.7 illustrates changes of the welfare measures with the social learning parameter γ_{42} ranging from the extreme case of no social learning (γ_{42} = 0) to γ_{42} = 1.10.

Figure 5.7: Welfare Measures for GM Technology Adoption by Changes in the Social Learning Parameter at the Aggregate Model



Unlike the relationship between welfare measures and risk aversion in Figure 5.6, the changes of the optimal value functions don't show monotonicity with respect to γ_{42}; $V\left(S \mid \Theta^{\gamma_{42}}\right)$ increases from the starting point γ_{42} = 0 and reaches a peak when γ_{42} = 0.80. And the value function drops from its peak to the endpoint γ_{42} = 1.10.

The evolution of value function as γ_{42} changes is presented in Table 5.8, which also reports the relative cost of social learning $\bar{C}_{social-learning}$.

Table 5.8: Welfare Measures and Costs of Social Learning at the Aggregate Model

Social Learning for GM Technology	The Optimal Value Function [a/]	Absolute Cost of Social Learning [b/]	Relative Cost of Social Learning (percent)
γ_{42}	$V\left(S \mid \Theta^{\gamma_{42}}\right)$	$C_{social-learning}$	$\bar{C}_{social-learning}$
0.00	35.62	2.33	6.55%
0.10	36.18	1.78	4.91%
0.20	36.66	1.29	3.53%
0.30	37.07	0.89	2.40%
0.40	37.39	0.56	1.51%
0.50	37.64	0.32	0.85%
0.60	37.81	0.15	0.39%
0.70	37.91	0.04	0.11%
0.80[c/d/]	37.96[c/]	0.00[c/]	0.00%[c/]
0.90	37.95	0.01	0.02%
1.00	37.89	0.06	0.17%
1.10	37.80	0.15	0.41%

Note: [a/ b/] Unit - $ hundred / acre
[c/] The baseline case at the minimum distance estimator
[d/] Social optimum γ_{42}^{*}

In the absence of social learning (γ_{42} = 0), $\bar{C}_{social-learning}$ amounts to 6.55%, indicating that farmers would pay 6.55% of the present value of their payoff to be able to learn from their neighbors in adopting GM technology. $\bar{C}_{social-learning}$ decreases gradually with increments of γ_{42}, with a minimum of 0% (social optimum) obtained at γ_{42}^{*} = 0.80. Then, $\bar{C}_{social-learning}$ rises slightly beyond this social optimum, indicating a range where farm welfare would start declining beyond that point. This identifies a region where social learning would be deemed “excessive” from a social viewpoint. These results also indicate that the amount of social learning used by farmers adopting GM technology is close to its optimum.

We have seen that the speed of GM technology adoption is monotonically reduced by increments in levels of social learning parameter γ_{42}. This was interpreted as an information externality in Section 5.3.2 (as free-riding on neighbors’ information provides a farmer an incentive to delay GM adoption). Our welfare results are qualitatively different. First, we find that, while increasing social learning from zero slows down GM adoption, it also tends to make the farmer better off. This reflects the fact that, by free-riding on the information provided by neighbors, the farmer can reduce its learning cost. Second, finding that the actual social learning is close to its optimum indicates that the farmers appear to have efficiently internalized the information externality associated with social learning. In other words, farmers have found a proper trade-off between individual learning and social learning in the process of adopting GM technology.

Chapter 6 : Results and Discussions of the Disaggregate GM Technology Adoption Models

This chapter presents the empirical results across three types of disaggregate models classified by farm type in terms of adoption pattern: the early-, the intermediate-, and the late- adopter. Considering heterogeneity ignored at the aggregate model (heterogeneity unrelated to initial conditions), the disaggregate DP models are presented to analyze heterogeneity in parameters across different sub-groups by farm type. With a focus on risk preferences and the relative role of individual/social learning, estimated parameters are reported for each type of adopter and compared across farm types. In addition, economic implications of models are discussed and evaluated together with sensitivity analyses on adoption path and welfare effects for each type of corn farmer.

Assuming that heterogeneity by farm type is attributed to different parameters across the disaggregate models, three sub-groups are classified from the DMR panel dataset according to adoption pattern: the early-, the intermediate-, and the late- adopter for GM corn as mentioned above. For each sub-group, parameter estimates obtained from the disaggregate model estimation are reported with a discussion of economic implications. In a way similar to the aggregate model in Chapter 5, the following analyses are done at the disaggregate model for each sub-group. First, hypothesis testing is implemented to examine selected scenarios evaluating the effects of risk aversion and social learning. Second, a sensitivity analysis is done investigating how adoption path changes with risk aversion and social learning. Third, a welfare analysis is conducted for evaluating the impacts of risk aversion and social learning on farm welfare. The following three sections present results and discussions of these analyses for the early adopter, the intermediate adopter, and the late adopter, in sequence. The last section compares results across farm types, discussing the presence of monotonicity in the effects of risk aversion and social learning for each type farmer's adoption patterns.

6.1.Early Adopter

6.1.1. Parameter Estimates and Adoption Curve

Following the discussion presented in Section 4.2.3, the parameter space of the early adopter's GM technology adoption model is represented as

$$\Theta^{EARLY} = \left\{ r^{EARLY}, \gamma_{11}^{EARLY}, \gamma_{21}^{EARLY}, \gamma_{32}^{EARLY}, \gamma_{42}^{EARLY} \right\}. \tag{6.1}$$

With a focus on the effects of risk aversion and individual/social learning on technology adoption, other parameters (besides the ones representing risk aversion and learning) are taken as given (β_{11}^{EARLY}, β_{22}^{EARLY}, and γ_{31}^{EARLY}). In practice, parameter estimates from the intermediate adopter's DP model are used as the fixed values for the early adopter's DP model. That is,

$$\beta_{11}^{EARLY} = \tilde{\beta}_{11}^{INTER}\ ,\ \beta_{22}^{EARLY} = \tilde{\beta}_{22}^{INTER}\ ,\ \text{and}\ \gamma_{31}^{EARLY} = \tilde{\gamma}_{31}^{INTER}, \qquad (6.2).$$

where $\tilde{\beta}_{11}^{INTER}$, $\tilde{\beta}_{22}^{INTER}$, and $\tilde{\gamma}_{31}^{INTER}$ are estimates obtained from the intermediate adopter's DP model using the minimum distance estimator. Then, the total number of parameters to be estimated in the early adopter's DP model reduces to 5 compared to the aggregate adoption model with 8 parameters. Parameter estimates are reported in Table 6.1.

The Arrow-Pratt absolute risk-aversion coefficient r^{EARLY} is estimated to be 0.08. Its positive sign reflects that the early adopter's risk preferences exhibit risk aversion; he/she perceives a new technology (GM seed) as a risky choice with uncertain profitability as average farmers do at the aggregate model. The analysis shows that early adopter's expected profit is estimated as \$8.59 million. And the Arrow-Pratt relative risk aversion coefficient $\overline{r}^{EARLY}$ is estimated as 0.69, which implies that his/her risk aversion seems to be low as $\bar{r}^{EARLY} < 1$ (Gollier, 2001, p. 31). Compared with $\bar{r}$ = 4.12 at the aggregate model, early adopters seem to be much less risk-averse in adopting GM seeds than average farmers. That is, early adopters exhibit lower risk aversion, which contributes to increasing their willingness to adopt GM technology.

Table 6.1: Parameter Estimates of the Early Adopter's GM Adoption Model

Parameter	Implication	Estimate
Reward Function		
r^{EARLY}	The Arrow-Pratt measure of absolute risk-aversion coefficient	0.08
$\bar{r}^{EARLY}$	The Arrow-Pratt measure of relative risk-aversion coefficient	0.69
System Equation		
β_{11}^{EARLY} a/	The effect of adoption of conventional technology on the average change in $\pi^{CONV,EARLY}$	0.11
β_{22}^{EARLY} b/	The effect of adoption of GM technology on the average change in $\pi^{GM,EARLY}$	2.50
Measurement Equation		
γ_{11}^{EARLY}	The effect of individual learning for conventional technology	1.26
γ_{21}^{EARLY}	The effect of social learning for conventional technology	0.85
γ_{31}^{EARLY} c/	The effect of yield for GM seed to $\pi^{CONV,EARLY}$	1.12
γ_{32}^{EARLY}	The effect of individual learning for GM technology	1.52
γ_{42}^{EARLY}	The effect of social learning for GM technology	0.17

Note: Goodness of fit is 0.0059.
[a/ b/ c/] Given from $\tilde{\beta}_{11}^{INTER}$, $\tilde{\beta}_{22}^{INTER}$, and $\tilde{\gamma}_{31}^{INTER}$

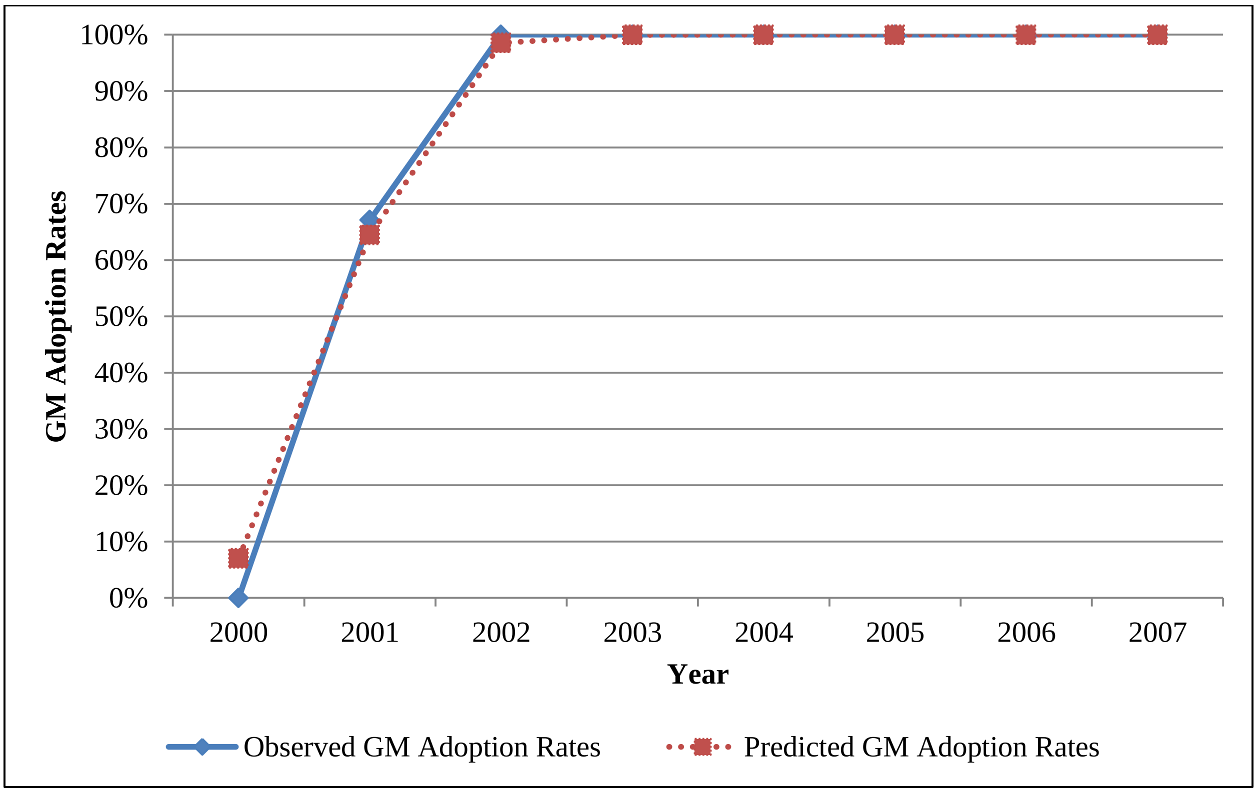
As described above, parameters in the system equation β_{11}^{EARLY} and β_{22}^{EARLY} are taken as given from the estimates in the intermediate adopter's DP model. They are all positive, reflecting that the adoption of conventional (GM) seeds improves profitability for the conventional (GM) technology. In addition, β_{22}^{EARLY} = 2.50 is greater than β_{11}^{EARLY} = 0.11, implying farmers perceive GM seed as more profitable on average than conventional seed. Compared with the result of the aggregate model (β_{11} = 2.20 and β_{22} = 2.50), the difference between β_{11}^{l} and β_{22}^{l} for each farm type l is shown to be rather large, reflecting that individual farmers at the disaggregate model may be more pessimistic about the old technology (conventional seed) compared to the new technology (GM seed).

Parameter estimates in the measurement equation are all positive as they are in the aggregate model. This means that there are positive impacts of both individual learning and social learning on the profitability for each technology. Estimated γ^{EARLY}'s are not so different from γ's estimated in the aggregate model except for the social learning parameter for GM technology γ_{42}^{EARLY} = 0.17, which is considerably smaller than γ_{42} = 0.80 at the aggregate model. This indicates that early adopters don't rely on their neighbors as much as average farmers do. In terms of information externalities, early adopters' incentive to delay adoption is thus weaker compared to average farmers' incentive, implying that early adopters tend to adopt GM technology more aggressively than average farmers.

Other findings are consistent with estimation results of the aggregate model reported in Section 5.1.1. The early adopter's individual learning parameter is also found to be greater than his/her social learning parameter for conventional technology ($\gamma_{11}^{EARLY} > \gamma_{21}^{EARLY}$) and for GM technology ($\gamma_{32}^{EARLY} > \gamma_{42}^{EARLY}$) (Conley and Udry, 2010; Munshi, 2004). Also, the early adopter's social learning parameter for conventional technology, γ_{21}^{EARLY} is higher than his/her social learning parameter for GM technology, γ_{42}^{EARLY}, reflecting that early adopters' knowledge also relies relatively more on social learning for conventional seeds than for GM seeds due to the shorter history of GM varieties and fewer neighbors who already adopted GM seeds in the early period of GM technology diffusion.

The predicted adoption rates of GM technology based on the parameter estimates in Table 6.1 are compared with selected early adopter's observed adoption rates from the DMR data as illustrated in Figure 6.1. Specific values for the goodness-of-fit (measured by squared discrepancies) for predicted adoption rates are presented in Table 6.2.

Figure 6.1: Observed and Predicted GM Adoption Rates for the Early Adopter, 2000-2007



Note: GM adoption rates are percentage of planted acres to GM seed.

The goodness-of-fit is close to zero as 0.0059, so that the early adopter's DP model for GM technology adoption fits the data very well. The only discrepancy occurs in 2000, when the DP model overestimates GM adoption rate by 7.03%. Against the aggregate model with a goodness-of-fit of 0.0303, the early adopter's DP model provides a better fit to the actual adoption rates of GM varieties. This result shows that, if different parameters from the aggregate model are applied, an alternative DP model (the disaggregate model for the early adopter) can fit the early adopter's adoption pattern much better than the aggregate model does. This provides some evidence supporting the presence of heterogeneity in parameters across groups.

Table 6.2: Observed and Predicted GM Adoption Rates for the Early Adopter, 2000-2007

Year	**Observed GM Adoption Rates**[a/]	**Predicted GM Adoption Rates**[b/]	**Squared Discepancies**[c/]
2000	0.00%	7.03%	0.0049
2001	67.10%	64.43%	0.0007
2002	100.00%	98.55%	0.0002
2003	100.00%	99.99%	0.0000
2004	100.00%	100.00%	0.0000
2005	100.00%	100.00%	0.0000
2006	100.00%	100.00%	0.0000
2007	100.00%	100.00%	0.0000
Sum of Squared Residuals (Goodness-of-fit statistic)			0.0059

Note: [a/ b/] GM adoption rates are percentage of planted acres to GM seed.
[c/] Squared residual c/ = $(a/ - b/)^2$

6.1.2. Hypothesis Testing

Focusing on the early adopter's risk preferences and individual/social learning, selected parameters are used to evaluate the statistical significance of the estimates. Hypothesis testing is done by simulating the early adopter's DP adoption model under alternative hypotheses. Scenario is denoted by sc, being hypothesized in the same way as done for the aggregate model in Section 5.2.1.[32]

[32] Full descriptions of each scenario are referred to Table 5.3 in Section 5.2.1.

Instead of investigating all scenarios, this section focuses on risk-aversion r^{EARLY} (Scenario 1) and the social learning parameter for GM technology adoption γ_{42}^{EARLY} (Scenario 3). The null hypothesis under Scenario 1 involves a counterfactual case where the early adopter's risk preferences exhibit risk neutrality ($H_0 : r^{EARLY} = 0$), with risk aversion as an alternative hypothesis. Also, the null hypothesis under Scenario 3 brings in a situation where social learning doesn't play any role in adopting GM technology for the early adopter ($H_0 : \gamma_{42}^{EARLY} = 0$).

As discussed in Section 5.2.2, hypothesis testing relies on the F-test. We consider the case where $N_{parameters}$ = 5 as we focus on the parameters for risk preferences and individual/social learning (r^{EARLY}, γ_{11}^{EARLY}, γ_{21}^{EARLY}, γ_{32}^{EARLY}, and γ_{42}^{EARLY}). Compared with the aggregate model with $N_{parameters}$ = 6, we have smaller number of parameters as other parameters (β_{11}^{EARLY}, β_{22}^{EARLY}, and γ_{31}^{EARLY}) are treated as constants for early adopters.

Denoting Θ^{EARLY} by the parameter space of the unrestricted nonlinear minimum distance estimator in Table 6.1, $\Theta_*^{EARLY,sc}$ indicates the parameter space of the estimator under the null hypothesis for each scenario. $SSR\left(\Theta^{EARLY}\right)$ and $SSR\left(\Theta_*^{EARLY,sc}\right)$ are the sum of squared residuals (goodness-of-fit statistic) under Θ^{EARLY} and $\Theta_*^{EARLY,sc}$, respectively. Table 6.3 presents results of hypothesis testing for each scenario.

Due to increased degrees of freedom for the denominator, the statistical significance is improved compared with the aggregate model. All the null hypotheses are rejected at the 1% or at the 5% significance level. Calculated F-statistics show different trends from the results of the aggregate model; the F-statistics under Scenario 2 and Scenario 4 are much higher than the F-statistics under any other scenarios, so that the effect of social learning for conventional technology γ_{21}^{EARLY} seems to be more important for the early adopter's GM adoption model compared to the aggregate adoption model. Also, rejections of null hypotheses for Scenario 5 and Scenario 6 indicate that the social learning parameter for conventional technology is different from the social learning parameter for GM technology.

Table 6.3: Results of Hypothesis Testing across Scenarios for the Early Adopter

Scenario *sc*	**Null Hypothesis**	**SSR(Θ^l)**[a/]	**SSR($\Theta_*^{l,sc}$)**[b/]	**df1**[c/]	**df2**[d/]	**F ^{SC} (df1, df2)**[e/]
1	$H_0 : r^{EARLY} = 0$	0.0059	0.0279	1	3	11.26**
2	$H_0 : \gamma_{21}^{EARLY} = 0$	0.0059	0.5823	1	3	295.11***
3	$H_0 : \gamma_{42}^{EARLY} = 0$	0.0059	0.0300	1	3	12.36**
4	$H_0 : \gamma_{21}^{EARLY} = 0 \,\&\, \gamma_{42}^{EARLY} = 0$	0.0059	2.5896	2	3	661.41***
5	$H_0 : \gamma_{21}^{EARLY} = \gamma_{42}^{EARLY} = 0.85$	0.0059	0.0993	2	3	23.91**
6	$H_0 : \gamma_{21}^{EARLY} = \gamma_{42}^{EARLY} = 0.17$	0.0059	0.5788	2	3	146.65***

Note: Statistical significance is denoted as *** at the 1% level, ** at the 5% level, and * at the 10% level.
[a/]: Goodness-of-fit statistic under Θ^l, $l = \{EARLY\}$
[b/]: Goodness-of-fit statistic under $\Theta_*^{l,sc}$, $l = \{EARLY\}$
[c/]: Degrees of freedom for the numerator
[d/]: Degrees of freedom for the denominator
[e/]: F-statistic

The null hypothesis $H_0 : r^{EARLY} = 0$ is rejected at the 5% significance level under Scenario 1, implying the early adopter's risk preferences exhibit risk aversion like average farmers in the aggregate model. For the social learning parameter for GM technology, the null hypothesis $H_0 : \gamma_{42}^{EARLY} = 0$ is rejected at the 5% significance level under Scenario 3, providing evidence that social learning plays an important role in the early adopter's GM technology adoption. From these results, hypothesis testing gives econometric evidence on the role of both risk aversion and social learning in GM technology adoption decisions.

6.1.3. Sensitivity Analysis on Adoption Path

The evaluation of the hypothesis testing results is expanded by conducting sensitivity analysis with a focus on impacts of risk aversion and social learning on GM technology adoption. We investigate how the early adopter's GM adoption curve varies with changes in two parameters: the risk aversion coefficient r^{EARLY} and the social learning parameter for GM technology γ_{42}^{EARLY}. Comparison with the aggregate model is also made to investigate farm heterogeneity reflecting how an early adopter's adoption pattern differs from average farmers' patterns.

We explore how the Arrow-Pratt absolute risk-aversion coefficient r^{EARLY} affects the speed of GM technology adoption for an early adopter. The early adopter's DP model for GM technology adoption is simulated at different levels of r^{EARLY} holding other parameters constant at their estimated values presented in Table 6.1. Figure 6.2 illustrates selected simulations of GM technology adoption over 8 years, with r^{EARLY} starting from risk neutrality r^{EARLY} = 0 to a high level of risk aversion, r^{EARLY} = 3.20. Specific values are presented in Table 6.4.

The early adopter's GM adoption at r^{EARLY} = 0.08 (the minimum distance estimates) is used as a benchmark curve represented as a dashed line in Figure 6.2. The figure shows that the GM adoption curves for early adopter are monotonically decreasing as the degree of risk aversion increases. That is, simulated GM adoption curves move downward as r^{EARLY} increases. Under risk neutrality, the GM adoption curve simulated with r^{EARLY} = 0 is at the most upper left among all simulated curves illustrated in Figure 6.2. This reflects that early adopters would adopt a new technology (GM corn varieties) very fast if their risk preferences exhibit risk neutrality. This documents how risk and risk aversion tend to slow down the adoption of GM technology on the U.S. corn grain farms.

Figure 6.2: Simulation of the GM Technology Adoption by Changes in Risk Aversion for the Early Adopter

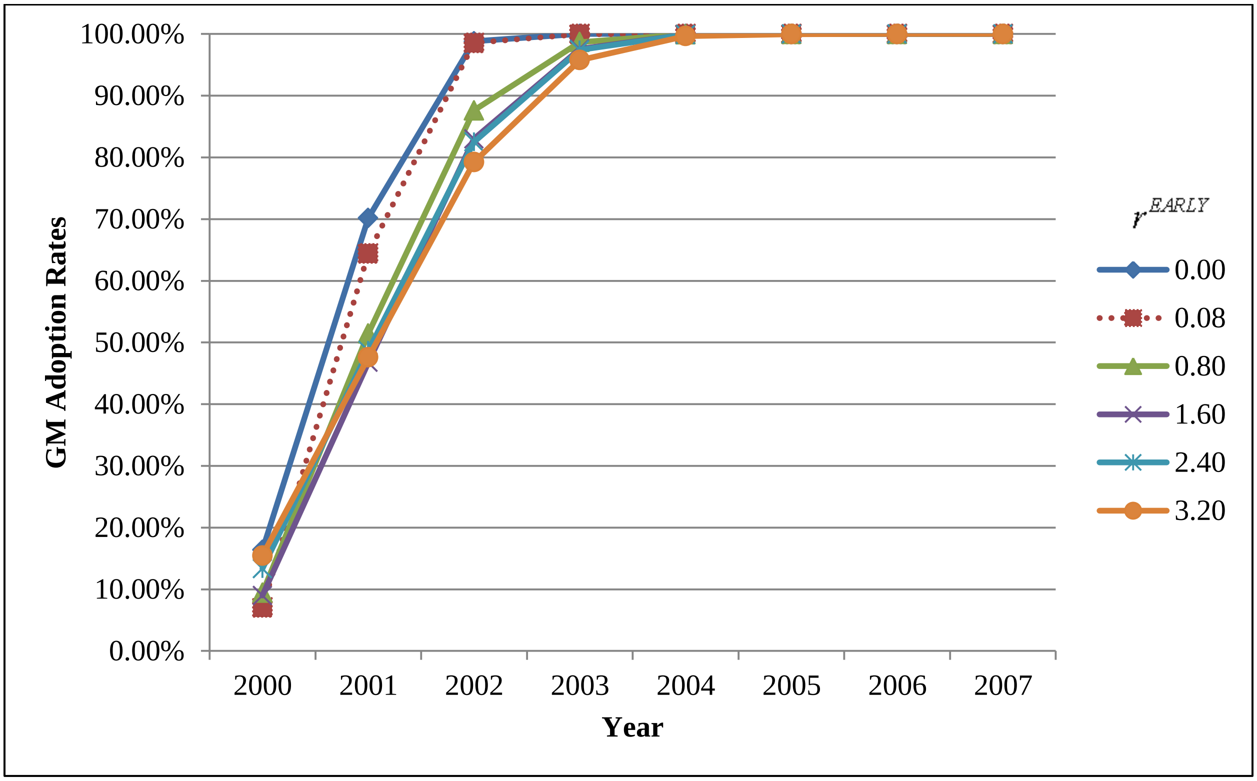
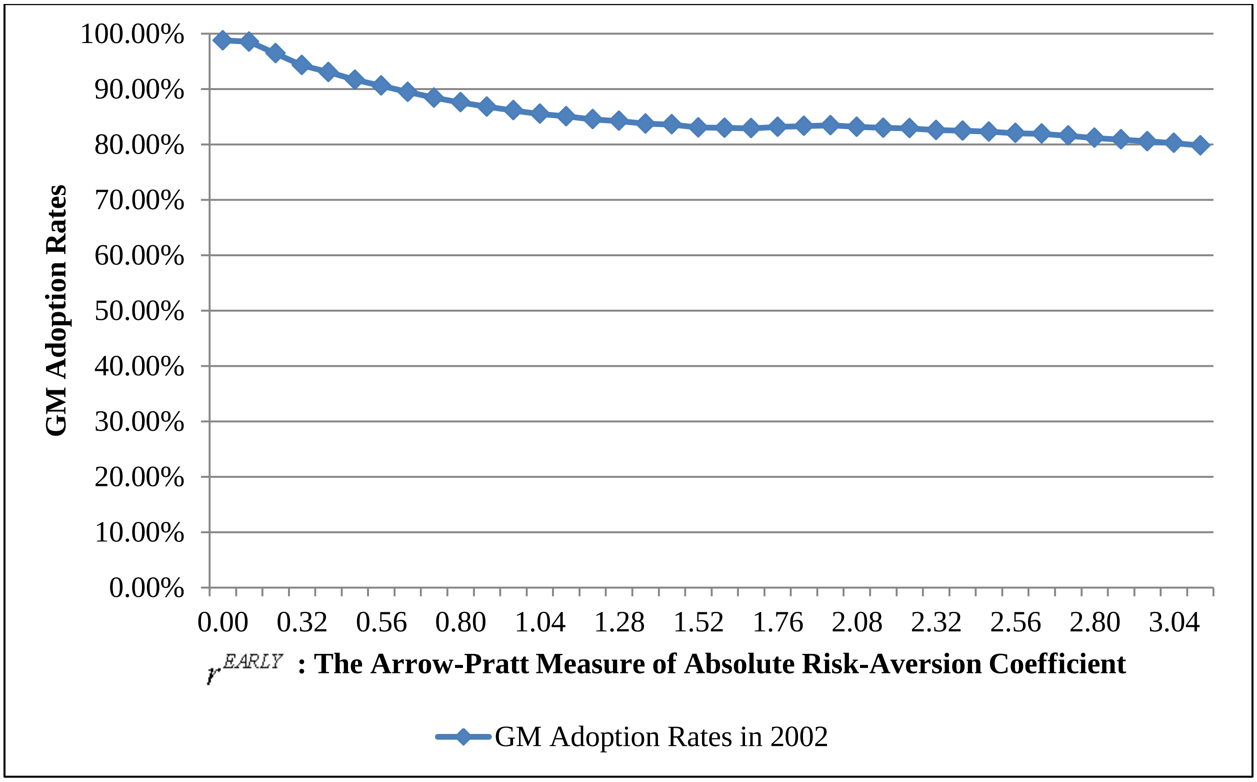


Table 6.4: Simulations of GM Technology Adoption by Changes in Risk Aversion for the Early Adopter

Risk Aversion	**Simulated GM Adoption Rates for the Early Adopter**								**Goodness-of-fit**
r^{EARLY}	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	
0.00	16.36%	70.18%	98.81%	100%	100%	100%	100%	100%	0.03
0.08	7.03%	64.43%	98.55%	99.99%	100%	100%	100%	100%	0.01
0.80	9.42%	51.47%	87.61%	98.68%	99.97%	100%	100%	100%	0.05
1.60	8.97%	46.76%	83.01%	97.57%	99.91%	100%	100%	100%	0.08
2.40	13.33%	48.68%	82.49%	97.42%	99.91%	100%	100%	100%	0.08
3.20	15.46%	47.61%	79.23%	95.78%	99.67%	99.98%	100%	100%	0.11

To evaluate further these effects, simulated adoption rates in the year 2002 are drawn in Figure 6.3 with r^{EARLY} ranging from 0.00 to 3.12 with increment of 0.08. The simulated GM adoption rate in 2002 decreases gradually from 98.80% under risk neutrality when r^{EARLY} = 0 to 79.82% when r^{EARLY} = 3.12. This finding is consistent with Liu (2008) stating that the more risk-averse farmers are, the slower they adopt a new technology.

Figure 6.3: Simulated GM Adoption Rates in 2002 by Changes in Risk Aversion for the Early Adopter



Farmers' heterogeneity is examined by comparing adoption patterns between early adopters and average farmers from the aggregate model. First, increases in risk aversion are found to reduce the adoption speed of GM technology monotonically for the early adopter. However, the effects of risk aversion on the adoption speed are not monotonic at the aggregate model; as discussed in Section 5.3.1, increments in risk aversion decrease adoption at a relatively higher level of r > 2.20 but increase adoption for lower levels of risk aversion (when r < 2.20).

Such different adoption patterns between the disaggregate model and the aggregate model provide evidence of significant heterogeneity among farmers. Unlike average farmers, early adopters may not consider diversifying strategies as a significant means of reducing uncertainty from risky technologies. Second, changes in adoption rates due to changes in risk aversion are smaller for the early adopter than for average farmers. In a similar range of risk aversion (for example, $0 < r, r^{EARLY} < 3.5$), movements of adoption curves for the early adopter in Figure 6.2 are not as wide as movements of average farmer's adoption curves in Figure 5.2. For example, at a fixed year 2003, the early adopter's simulated GM adoption rates change by at most 4.22% between $r^{EARLY} = 0$ and $r^{EARLY} = 3.20$ (Table 6.4). But GM adoption rates simulated at the aggregate model change by at most 20.22% between $r = 0.54$ and $r = 3.51$ in the same year (Table 5.5). This result shows that the early adopter is relatively insensitive to risk aversion in adopting GM technology compared to an average farmer in the aggregate model.

In sum, farmers' adoption behaviors and the effects of risk aversion show heterogeneity across farmers as follows. First, the impacts of risk aversion on GM adoption speed show a decreasing monotonicity for the early adopter but non-monotonicity for average farmers. Second, the role of portfolio selection in adopting risky technologies may not be as important for early adopters compared to average farmers. Third, early adopters are relatively less sensitive to risk aversion than average farmers.

Figure 6.4 and Table 6.5 present changes in simulated GM technology adoption curves by increases in the social learning parameter γ_{42}^{EARLY}, holding other parameters constant at their estimated value. The dashed line indicates the benchmark GM adoption curve for the early adopter when goodness-of-fit is best, with $\gamma_{42}^{EARLY} = 0.17$.

Figure 6.4: Simulation of the GM Technology Adoption by Changes in the Social Learning Parameter for the Early Adopter

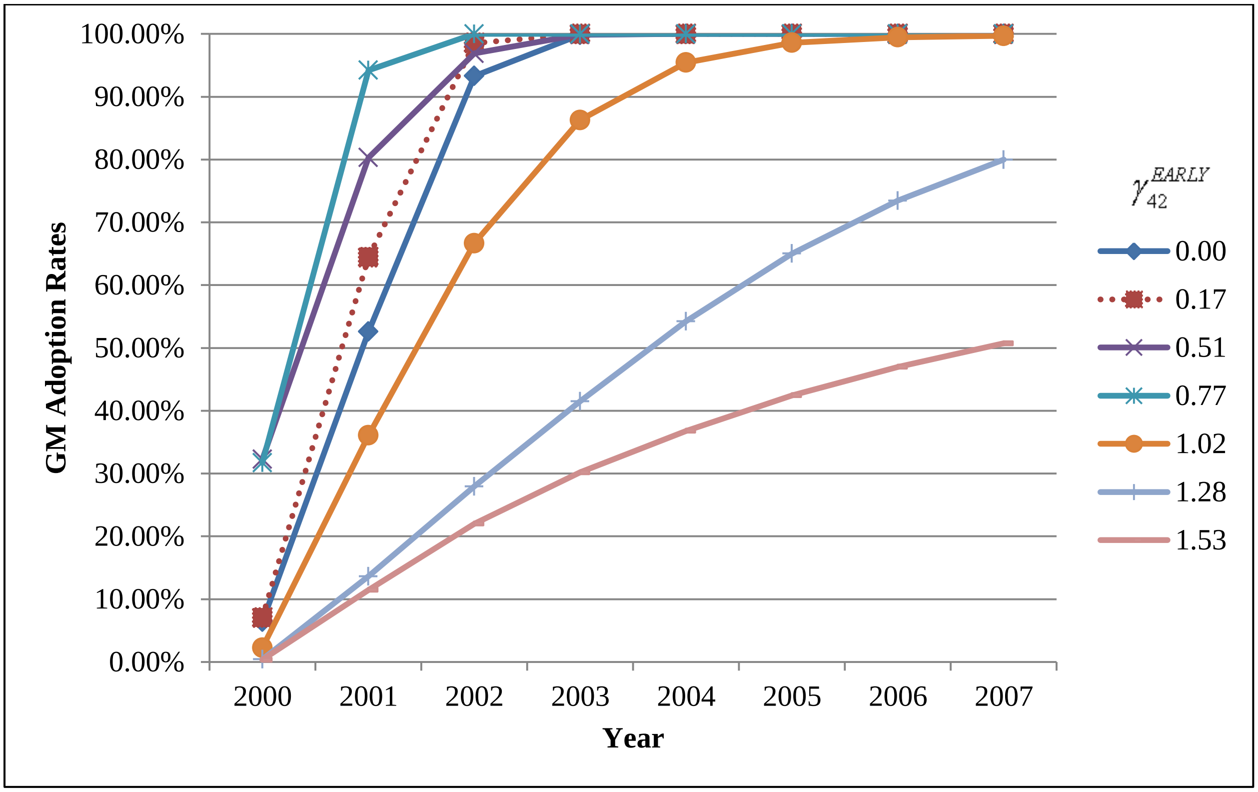


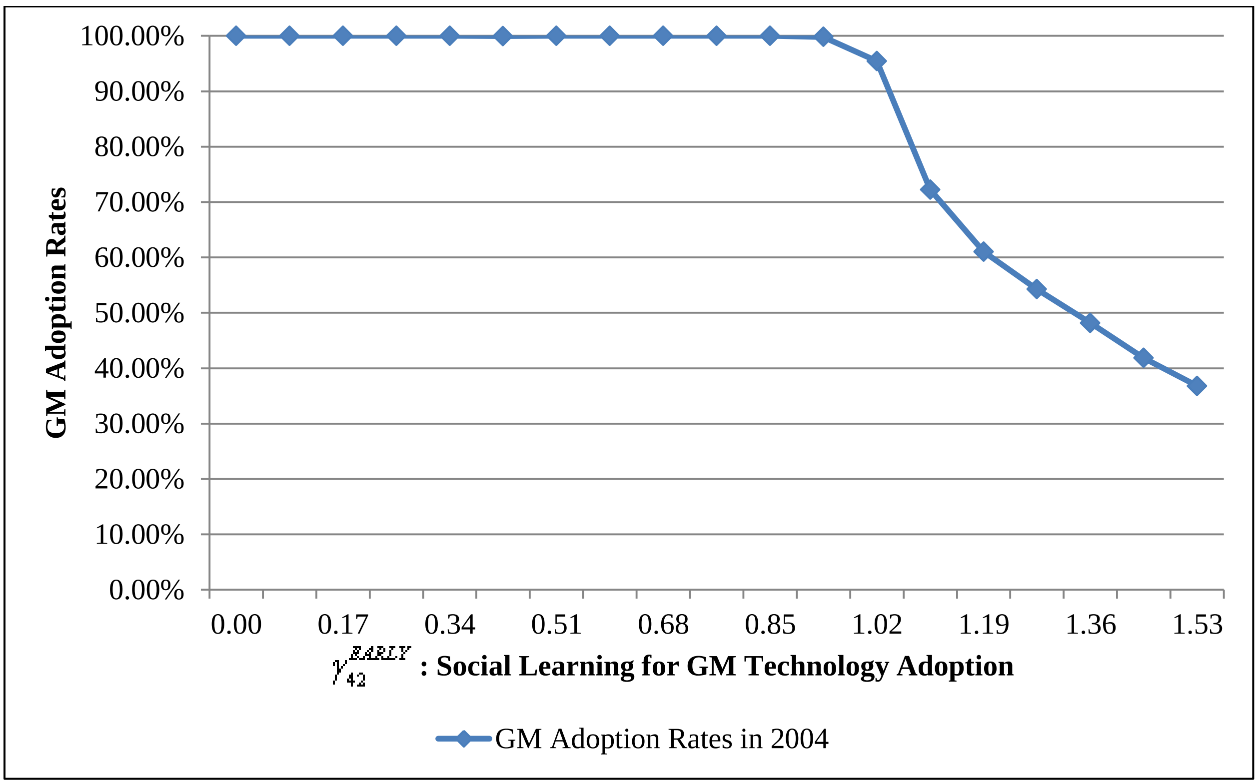
Table 6.5: Simulation of the GM Technology Adoption by Changes in the Social Learning Parameter for the Early Adopter

Social Learning	Simulated GM Adoption Rates for the Early Adopter								Goodness-of-fit
γ_{42}^{EARLY}	2000	2001	2002	2003	2004	2005	2006	2007	
0.00	6.39%	52.59%	93.30%	99.86%	100%	100%	100%	100%	0.03
0.17	7.03%	64.43%	98.55%	99.99%	100%	100%	100%	100%	0.01
0.34	23.65%	64.94%	93.43%	99.62%	100%	100%	100%	100%	0.06
0.51	32.27%	80.32%	96.90%	99.90%	100%	100%	100%	100%	0.12
0.68	36.24%	94.85%	100%	100%	100%	100%	100%	100%	0.21
0.85	23.07%	88.47%	99.58%	99.97%	100%	100%	100%	100%	0.10
1.02	2.24%	36.09%	66.70%	86.31%	95.46%	98.62%	99.46%	99.70%	0.23
1.19	0.40%	14.48%	30.52%	46.36%	61.03%	73.22%	82.29%	88.33%	1.32
1.36	0.38%	13.01%	26.10%	37.80%	48.16%	57.40%	64.73%	70.72%	1.89
1.53	0.34%	11.46%	22.03%	30.19%	36.80%	42.44%	46.99%	50.73%	2.66

But this effect is not monotonic: a smaller upward movement arises as γ_{42}^{EARLY} increases from zero. The smaller upward movement occurs only in the early period before 2002 at a relatively lower level of $\gamma_{42}^{EARLY} < 0.85$.

Overall, the impact of social interaction on the adoption speed is decreasing similar to average farmers' case at the aggregate model. This can be shown by evaluating the trend of simulated GM adoption rates in a particular year. Figure 6.5 illustrate how simulated GM adoption rates change as γ_{42}^{EARLY} increases in 2004.

Figure 6.5: Simulated GM Adoption Rates in 2004 by Changes in the Social Learning Parameter for the Early Adopter



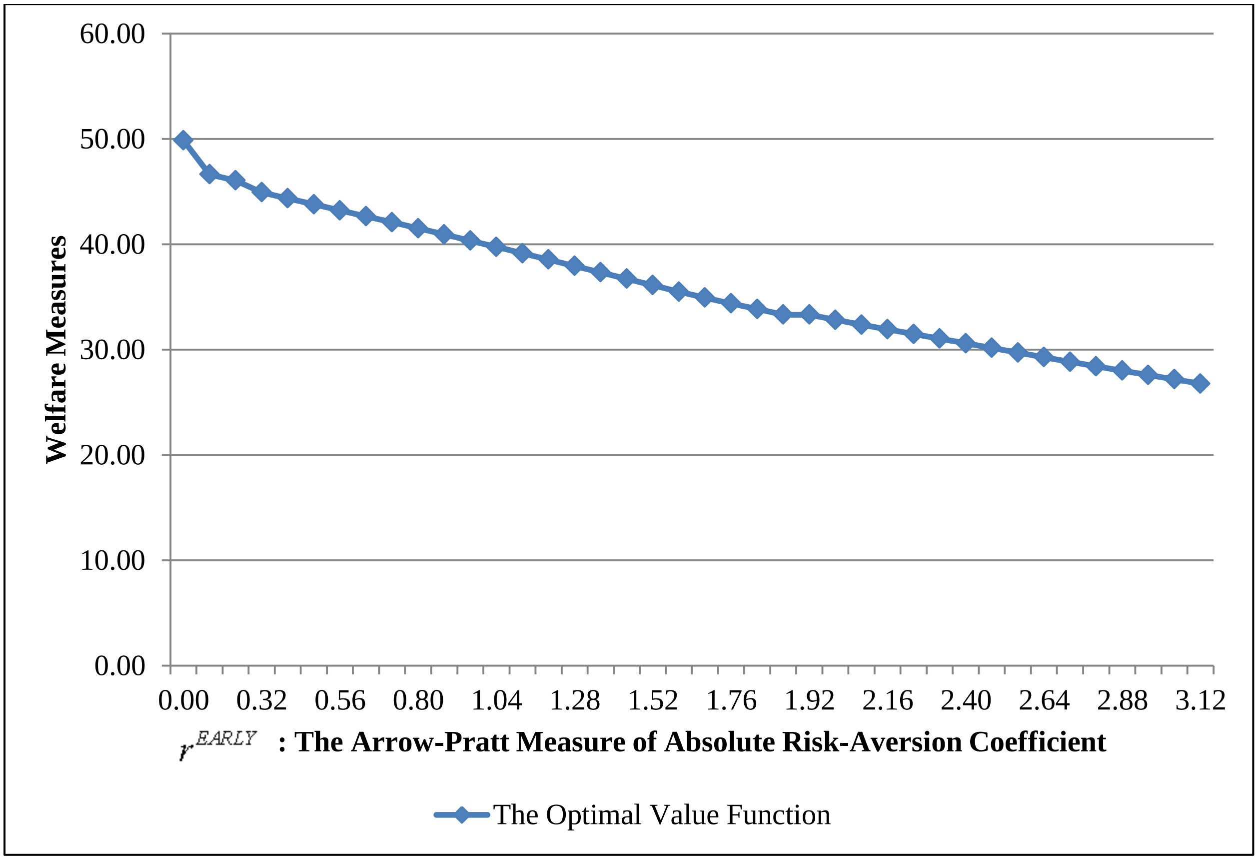
For example, a simulated GM adoption rate in 2004 falls to 36.80% for γ_{42}^{EARLY} = 1.53, compared with a full adoption of 99.99% for γ_{42}^{EARLY} = 0.17. Like the aggregate model, more intensive social learning for GM technology tends to slow down the speed of GM adoption for the early adopter, reflecting the presence of information externality (free-riding behavior). Thereby, early adopters also have an incentive to delay GM adoption.

The magnitude of incentive to delay (the strength of information externality) differs across farmers due to heterogeneity. Results show that this effect is smaller for the early adopter than for average farmers in the aggregate model. For example, in year 2004, simulated GM adoption rates for the early adopter change by at most 4.54% between γ_{42}^{EARLY} = 0 and γ_{42}^{EARLY} = 1.02 (Table 6.5). However, in the same year, simulated GM adoption rates for the representative farmer at the aggregate model change by at most 90.94% between γ_{42} = 0 and γ_{42} = 1.00 (Table 5.6). That is, early adopters are relatively less sensitive to the strength of information externality than average farmers in the aggregate model. This may occur because early adopters have fewer neighbors to learn from compared to average farmers and because they tend to rely relatively less on social learning. This provides evidence of heterogeneity in access and use of information among farmers.

6.1.4. Welfare Analysis

Value functions in the early adopter's DP simulations are analyzed under alternative scenarios related to risk aversion and social learning for GM technology. Following definitions in Section 5.4, a subscript or a superscript indexed by l is added to notations, where $l = \{EARLY\}$. It distinguishes the early adopter from the representative farmer in the aggregate model. In order to investigate the early adopter's value function, $V^{l}\left(S^{l}\,|\,\Theta^{l}\right)$ is evaluated at the points where each factor of S^{l} is closest to its average value in the starting year 2000, S^{l} = {3.57, 0.11, .3.57, 0.11}.[33] Figure 6.6 illustrates the changes of the optimal value functions at different levels of risk aversion for the early adopter.

Figure 6.6: Welfare Measures for GM Technology Adoption by Changes in Risk Aversion for the Early Adopter



33 For $l = \{EARLY\}$, the expected values in 2000 are 3.55 for $\mu^{CONV,l}$, 0.09 for $\sigma^2_{CONV,l}$, 3.64 for $\mu^{GM,l}$, and 0.12 for $\sigma^2_{GM,l}$.

Let the early adopter's value function under risk-neutrality be $V^l\left(S^l \mid \Theta^{r^l=0}\right)$. His/her baseline value function is represented as $V^l\left(S^l \mid \Theta^{r^l=0.08}\right)$ at the minimum distance estimator. Using (5.4), the early adopter's relative cost of risk aversion $\overline{C}_{risk-aversion}^{EARLY}$ is 6.90%, meaning that a risk-averse early adopter would pay 6.90% of the value function to eliminate all risk faced in the baseline case. Like the case at the aggregate model, the early adopter is made worse off compared to the case of risk-neutrality. This is consistent with the intuition that, under risk aversion, risk exposure has adverse impact on individual welfare. Table 6.6 provides $\overline{C}_{risk-aversion}^{EARLY}$ for simulated value functions (see Figure 6.6).

Table 6.6: Welfare Measures and Costs of Risk Aversion for the Early Adopter

Risk Aversion (Absolute)	**The Optimal Value Function**[a/]	**Absolute Cost of Risk Aversion**[b/]	**Relative Cost of Risk Aversion (percent)**
r^{EARLY}	$V^l\left(S^l \mid \Theta^{r^l}\right)$	$C_{risk-aversion}^{EARLY}$	$\overline{C}_{risk-aversion}^{EARLY}$
0.00	49.86	0.00	0.00%
0.08[c/]	46.64[c/]	3.22[c/]	6.90%[c/]
0.32	44.94	4.92	10.96%
0.56	43.23	6.63	15.34%
0.64	42.66	7.20	16.87%
0.88	40.94	8.92	21.78%
1.20	38.55	11.31	29.34%
1.52	36.12	13.74	38.05%
1.84	33.86	16.00	47.25%
2.08	32.38	17.48	53.99%
2.40	30.61	19.25	62.88%
2.72	28.84	21.02	72.87%
3.04	27.18	22.68	83.43%
3.12	26.77	23.09	86.23%

Note: $l = \{EARLY\}$

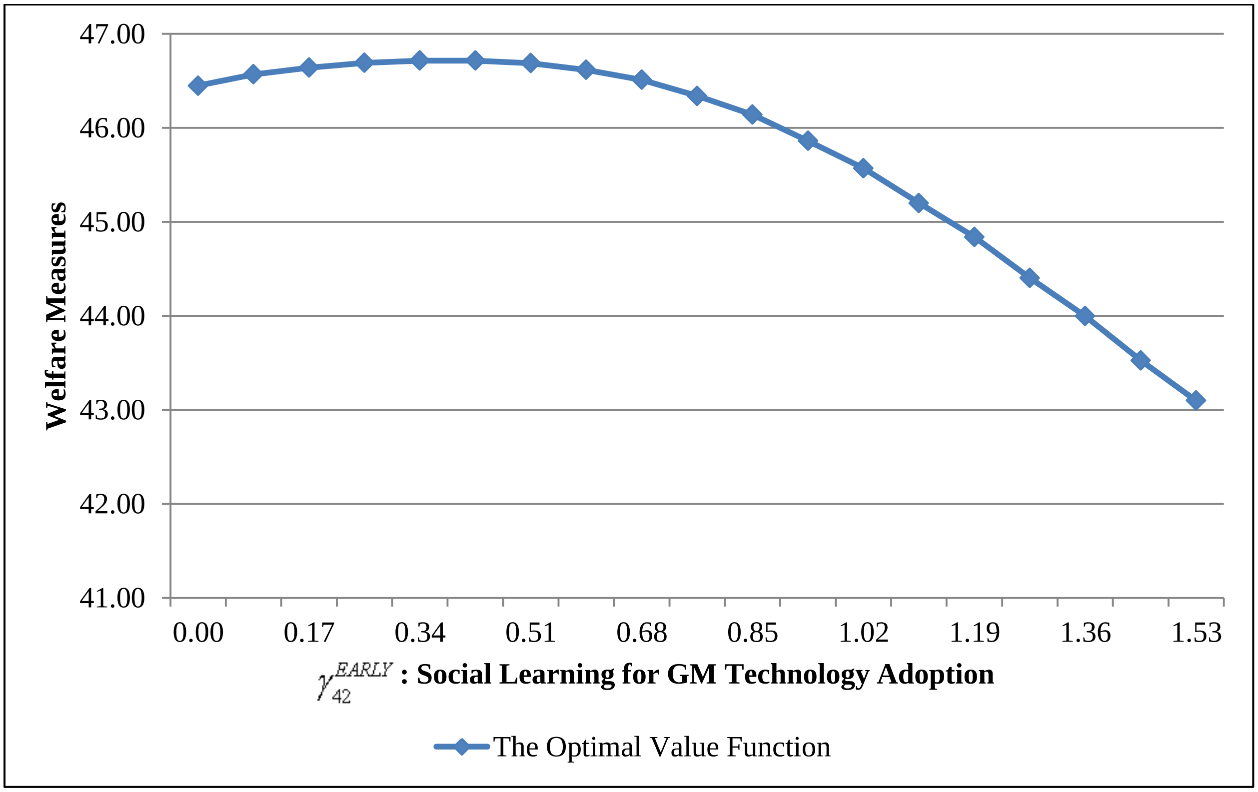
[a/] [b/] Unit - \$ hundred / acre

[c/] The baseline case at the minimum distance estimator

Results show a similar trend with simulation in the aggregate model. As discussed in Section 5.4.1, the early adopter's welfare declines monotonically as the level of risk aversion increases. Similarly, the cost of risk $\bar{C}^{EARLY}_{risk-aversion}$ increases monotonically with increments in r^{EARLY}, which means highly risk-averse early adopters would pay more to eliminate risk. In sum, like average farmers, early adopters are also made worse off if they are more risk averse.

Figure 6.7 illustrates how welfare measure changes with the social learning parameter γ^{EARLY}_{42} ranging from the extreme case of no social learning (γ^{EARLY}_{42} = 0) to γ^{EARLY}_{42} = 1.53.

Figure 6.7: Welfare Measures for GM Technology Adoption by Changes in the Social Learning Parameter for the Early Adopter



It shows that the relationship between welfare and γ_{42}^{EARLY} is non-monotonic. This trend is consistent with the welfare effects of γ_{42} in the aggregate adoption model as illustrated in Figure 5.7.

Let $\tilde{\gamma}_{42}^{EARLY}$ be the minimum distance estimator for γ_{42}^{EARLY} in the early adopter's DP model. Table 6.7 reports value functions obtained from simulations for different levels of γ_{42}^{EARLY} along with the relative cost of social learning $\bar{C}_{social-learning}^{EARLY}$.

Table 6.7: Welfare Measures and Costs of Social Learning for the Early Adopter

Social Learning for GM Technology	The Optimal Value Function [a/]	Absolute Cost of Social Learning [b/]	Relative Cost of Social Learning (percent)
γ_{42}^{EARLY}	$V^l\left(S^l \mid \Theta^{\gamma_{42}^l}\right)$	$C_{social-learning}^{EARLY}$	$\bar{C}_{social-learning}^{EARLY}$
0.00	46.45	0.27	0.58%
0.09	46.57	0.15	0.31%
0.17 [c/]	46.64 [c/]	0.07 [c/]	0.16% [c/]
0.26	46.69	0.02	0.05%
0.34	46.72	0.00	0.00%
0.43 [d/]	46.72 [d/]	0.00 [d/]	0.00% [d/]
0.51	46.69	0.03	0.06%
0.60	46.62	0.10	0.21%
0.68	46.51	0.20	0.44%
0.77	46.34	0.38	0.81%
0.85	46.14	0.58	1.25%
0.94	45.86	0.85	1.86%
1.02	45.57	1.14	2.51%
1.11	45.20	1.52	3.35%
1.19	44.84	1.88	4.19%
1.28	44.40	2.31	5.21%
1.36	44.00	2.72	6.18%
1.45	43.53	3.19	7.33%
1.53	43.10	3.62	8.39%

Note: $l = \{EARLY\}$

[a/] [b/] Unit - \$ hundred / acre

[c/] The baseline case at the minimum distance estimator $\tilde{\gamma}_{42}^{EARLY}$

[d] : Social optimum γ_{42}^{EARLY*}

The trend of $\bar{C}^{EARLY}_{social-learning}$ is consistent with the result obtained from the aggregate model presented in Table 5.8. When there is no social learning (γ^{EARLY}_{42} = 0), the early adopter would pay 0.58% of the present value of his/her payoff to be able to learn from their neighbors in adopting GM seeds.

Note that this amount is much less than the corresponding amount obtained from the aggregate model, $\bar{C}_{social-learning}$ = 6.55%. Thus, compared with average farmers, the early adopter's relative willingness to pay for social learning is much less. This seems to be associated with the result that the early adopter's social learning parameter $\tilde{\gamma}^{EARLY}_{42}$ = 0.17 is much less than the representative farmer's $\tilde{\gamma}_{42}$ = 0.80 at the minimum distance estimates. Intuitively, this indicates that early adopters tend to rely relatively less on social learning.

Results are similar to findings from the aggregate model. As γ^{EARLY}_{42} increases $\bar{C}^{EARLY}_{social-learning}$ decreases gradually, reaching a minimum of 0% (social optimum) at γ^{EARLY*}_{42} = 0.43. And $\bar{C}^{EARLY}_{social-learning}$ rises beyond γ^{EARLY*}_{42}, indicating that the early adopter's farm welfare would decline when social learning goes beyond the social optimum. As discussed in Section 5.4.2, excessive social learning could occur and make the early adopter worse off if reliance on social learning were to become "very large". In the aggregate model, the estimated social learning parameter $\tilde{\gamma}_{42}$ is identical to the representative farmer's social optimum γ^{*}_{42}. Whereas, in the early adopter's model, the estimated social learning parameter $\tilde{\gamma}^{EARLY}_{42}$ is not the same as the social optimum γ^{EARLY*}_{42}. But it is close to the social optimum: the early adopter would pay just 0.16% of his/her value function to reach the social optimum.

In sum, results indicate that the early adopter's welfare changes show similar trends to average farmers' welfare changes at the aggregate model. Increases in γ_{42}^{EARLY} slow down the adoption speed overall but make the early adopter better off due to the benefits of information externality – free-riding behavior. On the other hand, results show a few differences. First, in the absence of social learning, the early adopter's relative cost of social learning is much less than what average farmers pay at the aggregate model. This reflects that the magnitude and cost/benefit of social learning for the early adopter is relatively small compared to average farmers. Second, the early adopter's actual social learning is not the social optimum while the average farmer's social learning is consistent with social optimum. This indicates the potential for welfare gains from social learning by early adopters. But the magnitude of these gains is estimated to be small as only 0.16% of his/her welfare.

6.2.Intermediate Adopter

6.2.1. Parameter Estimates and Adoption Curve

The intermediate adopter's DP model involves 8 parameters including the effects of conventional (GM) technology on the average change in the profitability for conventional (GM) seed, β_{11}^{INTER} (β_{22}^{INTER}) and the effects of yield performance of GM seed on the profitability for conventional seed γ_{31}^{INTER} like the aggregate model. As described in the previous section, MDE estimates $\tilde{\beta}_{11}^{INTER}$, $\tilde{\beta}_{22}^{INTER}$, and $\tilde{\gamma}_{31}^{INTER}$ are treated as constant for the early- and the late- adopter's DP models. Estimation results are presented in Table 6.8.

Absolute risk-aversion coefficient r^{INTER} is estimated to be 0.35, indicating an intermediate adopter is risk averse. With his/her average profit level \$8.32 million for 8 years, the relative risk-aversion coefficient $\overline{r}^{INTER}$ is calculated to be 2.91. This shows that the intermediate adopter's magnitude of risk-aversion is at a medium level as it is less than 5 (Gollier, 2001, p. 31). Estimated β_{11}^{INTER} and β_{22}^{INTER} are all positive, indicating that adoption of each seed at the current year improves the profitability for each seed in the following year. Compared with the aggregate model, the effect of GM adoption on its profitability β_{22}^{INTER} is estimated to be the same as the corresponding parameter at the aggregate model β_{22} = 2.50.

Table 6.8: Parameter Estimates of the Intermediate Adopter's GM Adoption Model

Parameter	Implication	Estimate
Reward Function		
r^{INTER}	The Arrow-Pratt measure of absolute risk-aversion coefficient	0.35
$\bar{r}^{INTER}$	The Arrow-Pratt measure of relative risk-aversion coefficient	2.91
System Equation		
β_{11}^{INTER}	The effect of adoption of conventional technology on the average change in $\pi^{CONV,INTER}$	0.11
β_{22}^{INTER}	The effect of adoption of GM technology on the average change in $\pi^{GM,INTER}$	2.50
Measurement Equation		
γ_{11}^{INTER}	The effect of individual learning for conventional technology	0.72
γ_{21}^{INTER}	The effect of social learning for conventional technology	0.55
γ_{31}^{INTER}	The effect of yield for GM seed to $\pi^{CONV,INTER}$	1.12
γ_{32}^{INTER}	The effect of individual learning for GM technology	1.35
γ_{42}^{INTER}	The effect of social learning for GM technology	0.94

Note: Goodness of fit is 0.0523.

However, the effect of conventional seed adoption on its profitability β_{11}^{INTER} = 0.11 is much less than that of the aggregate model β_{11} = 2.20. This reflects that the selected intermediate adopter is more pessimistic about the profitability of conventional seed than average farmers in the aggregate model.

All the signs of γ's are estimated to be positive, implying that both individual learning and social learning positively affect profitability for each technology. Especially, the social learning parameter γ_{42}^{INTER} is related to the strength of information externalities. It is estimated to be 0.94, which is much larger than γ_{42}^{EARLY} = 0.17 at the early adopter's model and slightly larger than γ_{42} = 0.80 for average farmers at the aggregate model. Intuitively, we can infer that the intermediate adopter is affected more by social interaction than the early adopter. This will be further discussed in Section 6.4. Comparing the relative roles of learning, the effects of individual learning are shown to be greater than the effects of social learning for each technology ($\gamma_{11}^{INTER} > \gamma_{21}^{INTER}$ for conventional technology and $\gamma_{32}^{INTER} > \gamma_{42}^{INTER}$ for GM technology) as the previous literature has shown. The positive value of γ_{31}^{INTER} indicates that GM traits may be incorporated in "high quality" conventional seed to improve yield.

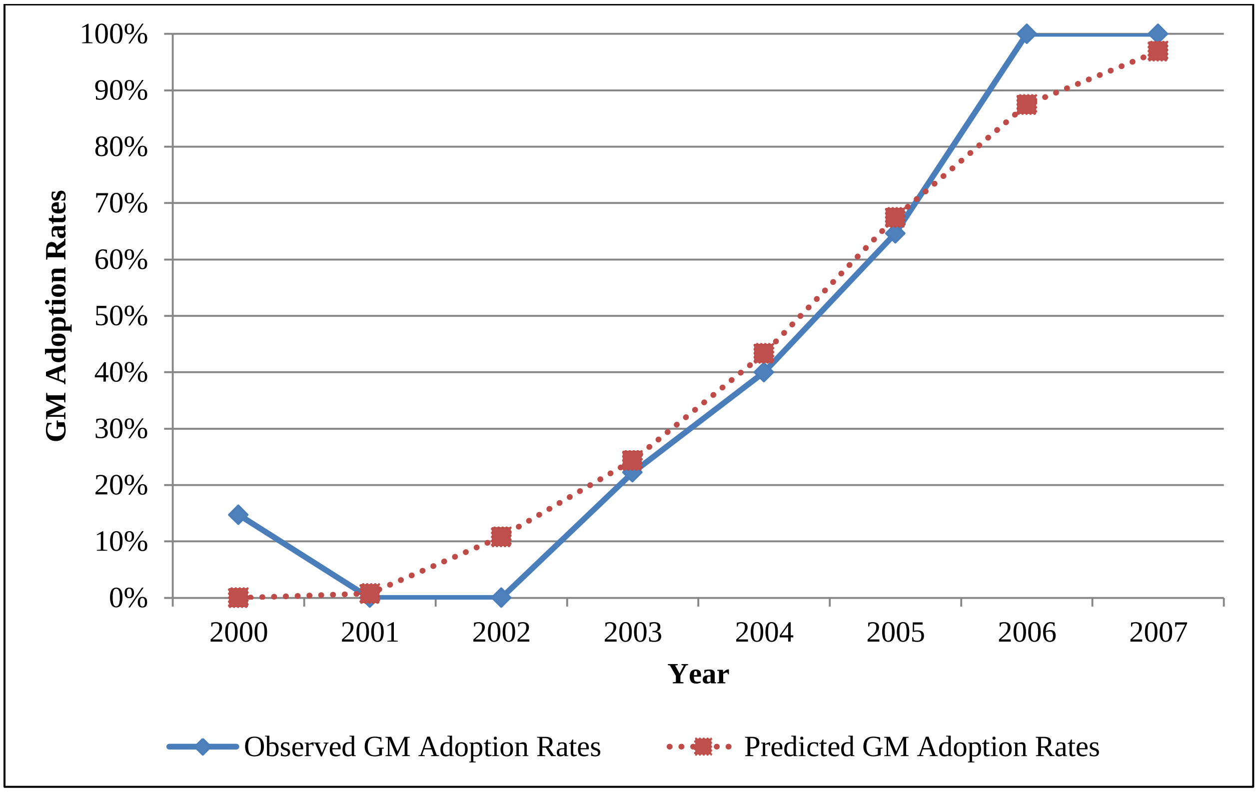
The goodness-of-fit of the model is reported as 0.0523. As shown in Table 6.9 and Figure 6.8, the model fits the intermediate farmer's observed adoption path moderately well.

Table 6.9: Observed and Predicted GM Adoption Rates for the Intermediate Adopter, 2000-2007

Year	Observed GM Adoption Rates[a/]	Predicted GM Adoption Rates[b/]	Squared Residual[c/]
2000	14.71%	0.00%	0.0216
2001	0.00%	0.76%	0.0001
2002	0.00%	10.79%	0.0116
2003	22.22%	24.36%	0.0005
2004	40.00%	43.33%	0.0011
2005	64.62%	67.46%	0.0008
2006	100.00%	87.49%	0.0157
2007	100.00%	96.93%	0.0009
Sum of Squared Residuals (Goodness-of-fit statistic)			0.0523

Note: [a/ b/] GM adoption rates are percentage of planted acres to GM seed.
[c/] Squared residual c/ = $(a/ – b/)^2$

Figure 6.8: Observed and Predicted GM Adoption Rates for the Intermediate Adopter, 2000-2007



Note: GM adoption rates are percentage of planted acres to GM seed.

6.2.2. Hypothesis Testing

We focus on the effects of risk aversion and the social learning parameter for GM technology. Table 6.10 presents results of the hypothesis testing using F-tests. Except for Scenario 5, all the null hypotheses are rejected at the 5% level (Scenario 1, Scenario 2, Scenario 4, and Scenario 6) and at the 1% level (Scenario 3). The null hypothesis for the intermediate farmer's risk aversion $H_0 : r^{INTER} = 0$ under Scenario 1 is rejected at the 5% level. By rejecting risk neutrality strongly, this provides econometric evidence that the intermediate adopter's risk preferences exhibit risk aversion. The null hypothesis for the social learning parameter γ_{42}^{INTER} under Scenario 3 corresponds to a situation where social learning doesn't play any role in GM technology adoption. Testing result shows that $H_0 : \gamma_{42}^{INTER} = 0$ is rejected at the 1% level. Thus, the presence of social learning effects on GM adoption is also strongly supported for the intermediate adopter with high statistical significance.

Table 6.10: Results of Hypothesis Testing across Scenarios for the Intermediate Adopter

Scenario *sc*	Null Hypothesis	SSR(Θ^l)[a/]	SSR($\Theta_*^{l,sc}$)[b/]	df1[c/]	df2[d/]	F ^{sc} (df1, df2)[e/]
1	$H_0 : r^{INTER} = 0$	0.0523	0.6935	1	2	24.52**
2	$H_0 : \gamma_{21}^{INTER} = 0$	0.0523	1.9210	1	2	71.45**
3	$H_0 : \gamma_{42}^{INTER} = 0$	0.0523	2.6594	1	2	99.68***
4	$H_0 : \gamma_{21}^{INTER} = 0 \,\&\, \gamma_{42}^{INTER} = 0$	0.0523	3.8177	2	2	71.98**
5	$H_0 : \gamma_{21}^{INTER} = \gamma_{42}^{INTER} = 0.55$	0.0523	0.1115	2	2	1.13
6	$H_0 : \gamma_{21}^{INTER} = \gamma_{42}^{INTER} = 0.94$	0.0523	1.8401	2	2	34.18**

Note: Statistical significance is denoted as *** at the 1% level, ** at the 5% level, and * at the 10% level.
[a/]: Goodness-of-fit statistic under Θ^l , $l = \{INTER\}$
[b/]: Goodness-of-fit statistic under $\Theta_*^{l,sc}$, $l = \{INTER\}$
[c/]: Degrees of freedom for the numerator
[d/]: Degrees of freedom for the denominator
[e/]: F-statistic

6.2.3. Sensitivity Analysis on Adoption Path

As mentioned in the previous section, the presence of risk-aversion is statistically significant for intermediate adopters. This raises the question: how is the speed of GM technology adoption affected by increments in the absolute risk-aversion coefficient r^{INTER}? Figure 6.9 and Table 6.11 report simulated adoption rates of GM technology under alternative risk aversion parameters r^{INTER}, holding other parameters constant.

The simulation at the minimum distance estimator (benchmark case) is drawn with a dashed line in Figure 6.9. Starting from the benchmark case r^{INTER} = 0.35, the adoption curve moves to the upper-left up to r^{INTER} = 1.05 and then moves to the down-right beyond that level up to r^{INTER} = 3.55.

Figure 6.9: Simulation of the GM Technology Adoption by Changes in Risk Aversion for the Intermediate Adopter

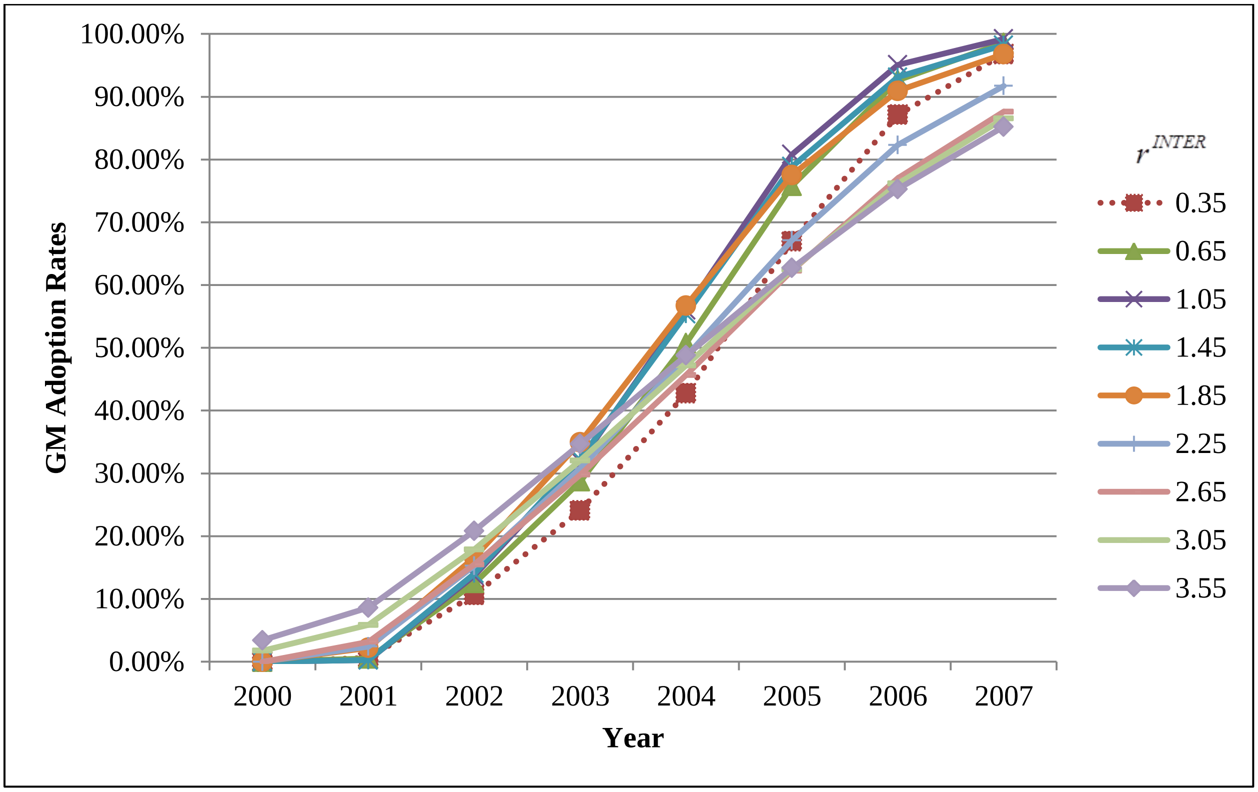


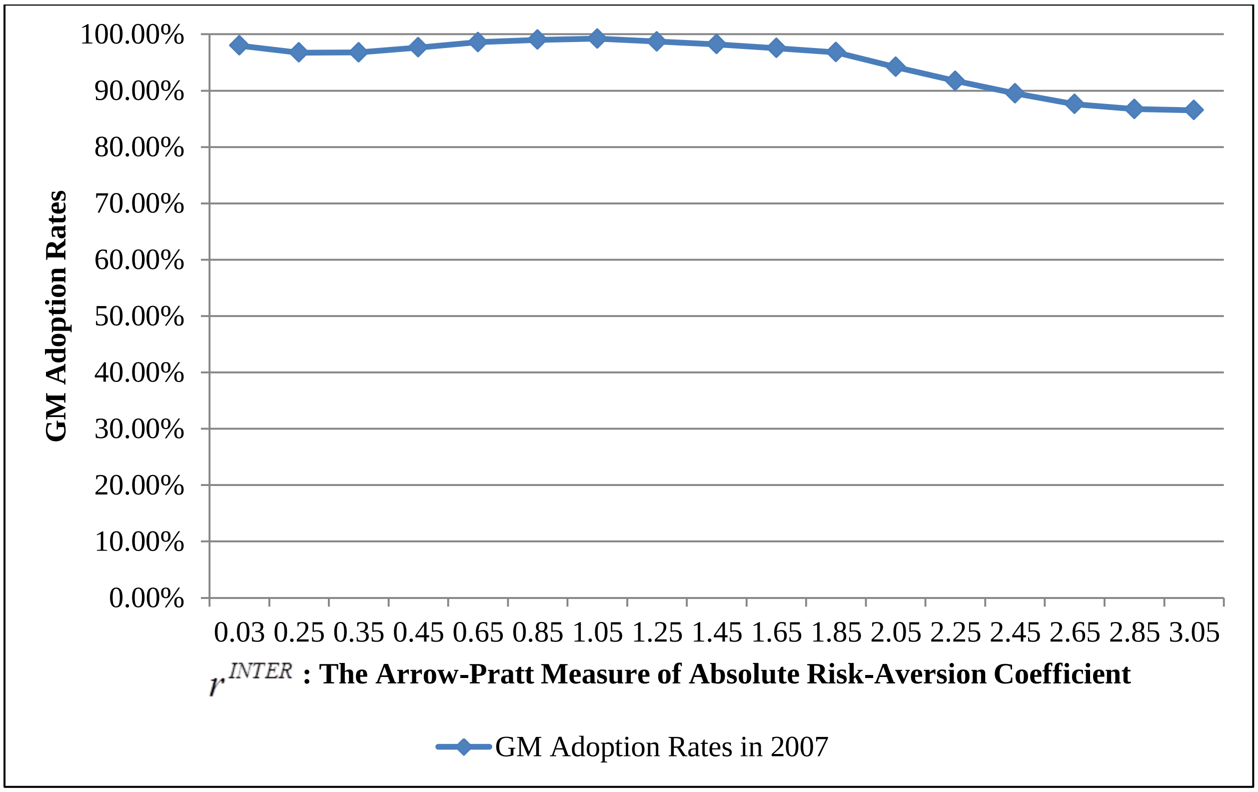
Table 6.11: Simulations of GM Technology Adoption by Changes in Risk Aversion for the Intermediate Adopter

Risk Aversion	Simulated GM Adoption Rates for the Intermediate Adopter								Goodness-of-fit
r^{INTER}	2000	2001	2002	2003	2004	2005	2006	2007	
0.35	0.00%	0.63%	10.66%	24.07%	42.73%	66.94%	87.13%	96.76%	0.06
0.65	0.00%	0.51%	12.50%	28.72%	50.75%	75.78%	92.64%	98.58%	0.09
1.05	0.00%	0.26%	13.71%	31.93%	56.02%	80.81%	95.08%	99.21%	0.12
1.45	0.00%	0.23%	14.04%	32.27%	55.38%	78.88%	93.12%	98.22%	0.12
1.85	0.00%	2.22%	16.63%	34.95%	56.72%	77.53%	90.93%	96.79%	0.13
2.25	0.00%	2.42%	15.30%	30.81%	48.62%	67.12%	82.32%	91.72%	0.10
2.65	0.00%	3.18%	15.48%	29.80%	45.67%	62.29%	77.04%	87.62%	0.12
3.05	1.75%	5.86%	17.88%	32.05%	47.20%	62.48%	76.18%	86.52%	0.14

This movement indicates changes in GM seed adoption are non-monotonic as the magnitude of risk aversion varies in the intermediate adopter's DP model. The adoption of GM seed increases with risk aversion r^{INTER} up to 1.05 and decreases beyond that point. This trend is similar to the result obtained from the aggregate model, reflecting that the intermediate adopter tries to reduce risk by diversifying adoption choices when he/she perceives both conventional and GM technologies are risky choices (Anderson et al., 1977).

Figure 6.10 illustrates changes of GM adoption rates in 2007 as r^{INTER} increases from a very low level 0.03 to a considerably high level 3.05.

Figure 6.10: Simulated GM Adoption Rates in 2007 by Changes in Risk Aversion for the Intermediate Adopter

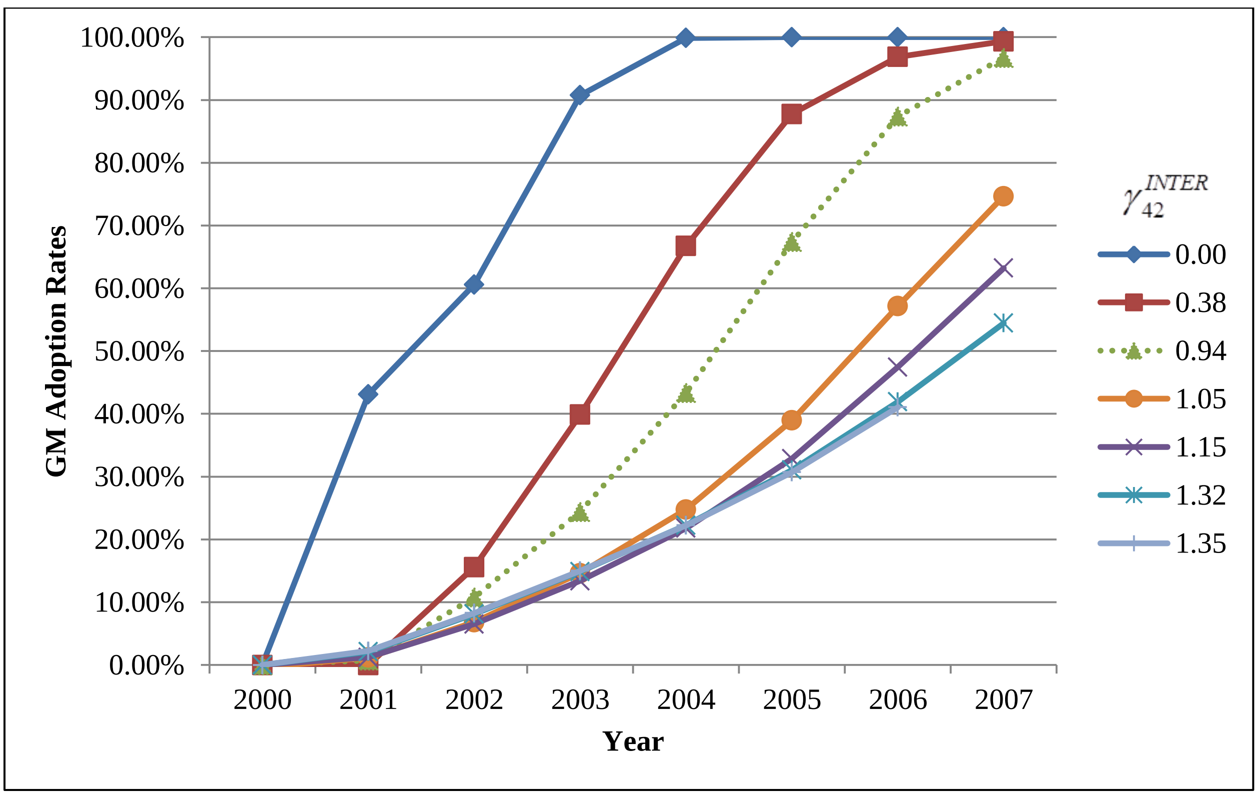


Though the changes are small within the interval, the trend reflects the potential role of farm portfolio selection. Note that the early adopter's DP model is monotonically decreasing by increments in risk aversion r^{EARLY}. Thereby, empirical results show that there exists heterogeneity in risk preferences across groups. That is, adoption pattern and the role of risk and risk-aversion appear to be different across farm types between the early adopter and the intermediate adopter.

Though the adoption pattern in terms of r^{INTER} in the intermediate adopter's model is similar to that in the aggregate model, there are differences. In 2007, given changes in r^{INTER} ranging from 0 to 3.50, the induced changes of adoption rates in Table 6.11 for the intermediate adopter are relatively small compared to the ones in Table 5.5. For example, in year 2007, the largest induced change in adoption rates is just 12.69% in Table 6.11, which is much less than the change of 34.29% in Table 5.5.

As illustrated in Figure 6.11, the movements of simulated adoption curves are monotonically decreasing in γ_{42}^{INTER} unlike the case of risk aversion.

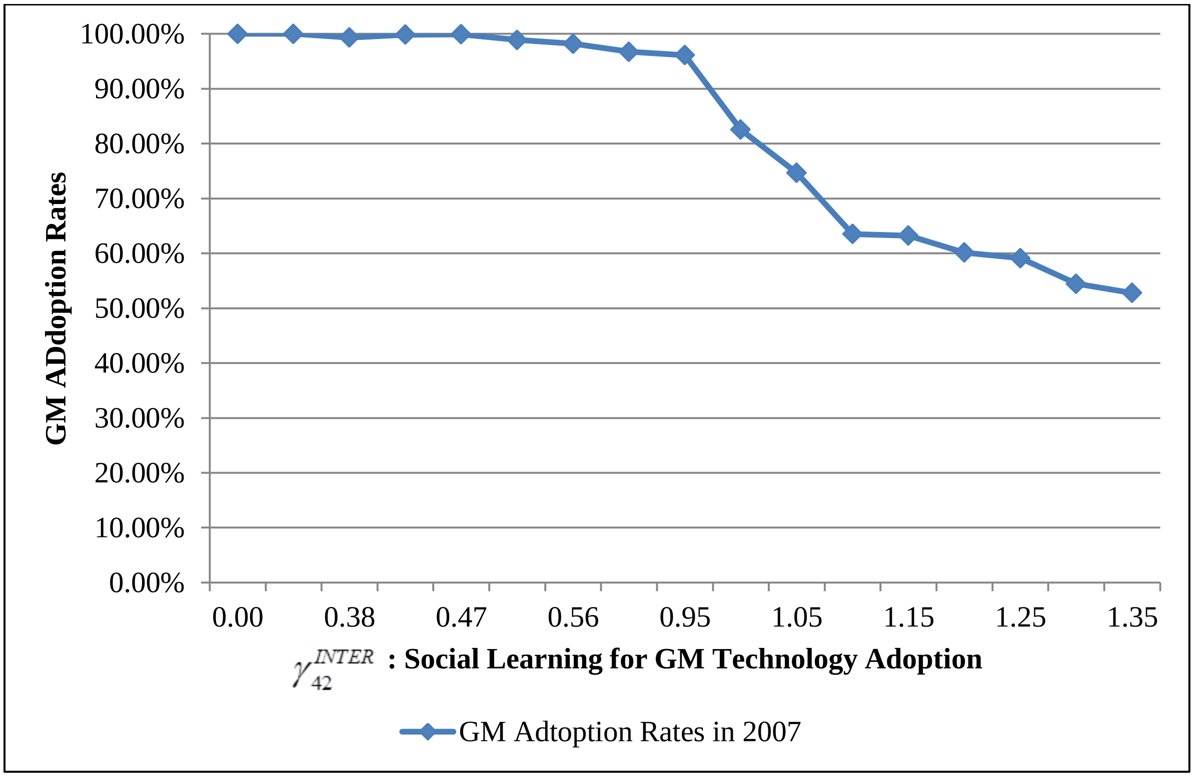
Figure 6.11: Simulation of the GM Technology Adoption by Changes in the Social Learning Parameter for the Intermediate Adopter



As γ_{42}^{INTER} increases from an extreme case of no social learning ($\gamma_{42}^{INTER} = 0$) to the same level as for individual learning $\gamma_{42}^{INTER} = \gamma_{32}^{INTER} = 1.35$, Figure 6.11 shows the same trends as the aggregate model and the early adopter's model; simulated adoption curves move from the upper-left to the down-right as γ_{42}^{INTER} increases, indicating increments in γ_{42}^{INTER} slow down the GM adoption.

Figure 6.12 illustrates an intuitive relation between the social learning parameter and GM adoption rates in 2007. It shows that relying more on social learning slows down GM adoption, reflecting the presence of information externalities. The intermediate adopter has an incentive to delay the GM adoption by free-riding on the information provided by his/her neighbors.

Figure 6.12: Simulated GM Adoption Rates in 2007 by Changes in the Social Learning Parameter for the Intermediate Adopter



6.2.4. Welfare Analysis

To evaluate how farm welfare changes with risk aversion, the optimal value functions are simulated in the intermediate adopter's DP model by changing the risk-aversion coefficient r^{INTER}, holding other parameters constant. Figure 6.13 illustrates that increasing risk aversion decreases welfare. This is intuitive and reflects that risk and risk aversion tend to reduce the intermediate adopter's welfare.

Figure 6.13: Welfare Measures for GM Technology Adoption by Changes in Risk Aversion for the Intermediate Adopter

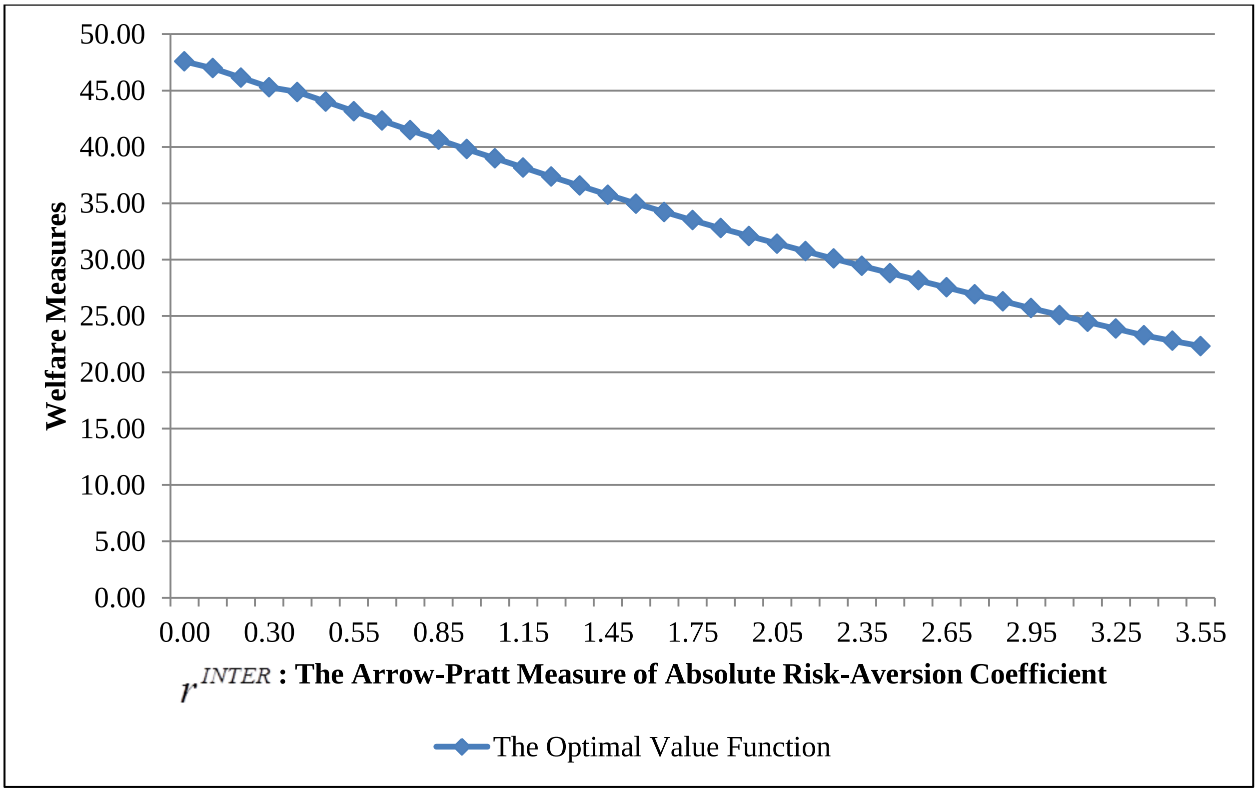


Table 6.13 reports the relative cost of risk aversion $\bar{C}^{INTER}_{risk-aversion}$ measuring the relative amount a farmer is willing to pay to eliminate his/her risk exposure. At the baseline case (r^{INTER} = 0.35), the intermediate adopter would pay 6.05% of his/her expected payoff. The relative

amount he/she would pay increases as r^{INTER} increases. That is, the intermediate adopter is made worse off as he/she is more risk averse.

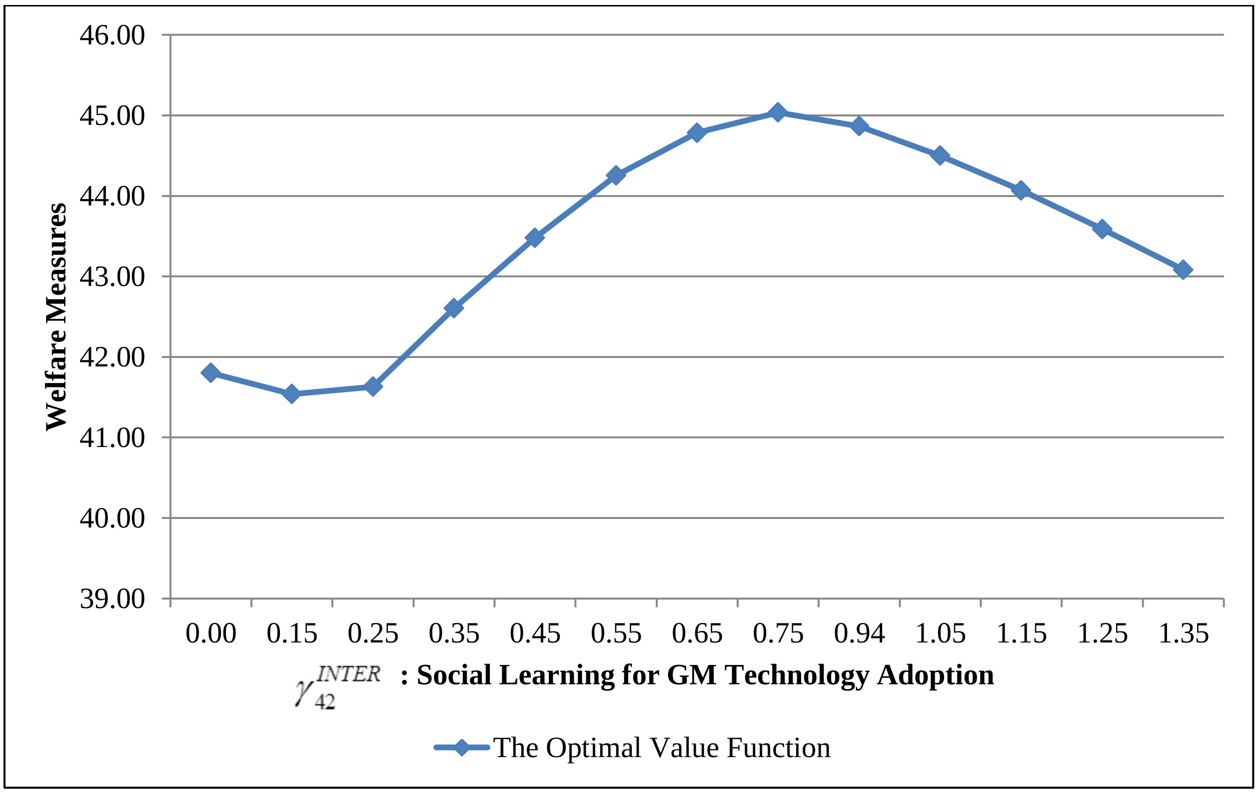
Table 6.12: Welfare Measures and Costs of Risk Aversion for the Intermediate Adopter

Risk Aversion (Absolute)	The Optimal Value Function[a/]	Absolute Cost of Risk Aversion[b/]	Relative Cost of Risk Aversion (percent)
r^{INTER}	$V^l\left(S^l \mid \Theta^{r^l}\right)$	$C^{INTER}_{risk-aversion}$	$\bar{C}^{INTER}_{risk-aversion}$
0.00	47.58	0.00	0.00%
0.20	46.14	1.44	3.13%
0.35[c/]	44.87[c/]	2.72[c/]	6.05%[c/]
0.65	42.32	5.26	12.43%
0.95	39.80	7.78	19.54%
1.25	37.36	10.22	27.34%
1.55	34.96	12.63	36.12%
1.85	32.79	14.79	45.11%
2.15	30.74	16.84	54.78%
2.45	28.79	18.79	65.24%
2.75	26.92	20.66	76.78%
3.05	25.08	22.50	89.74%

Note: $l = \{INTER\}$
[a/] [b/] Unit - \$ hundred / acre
[c/] The baseline case at the minimum distance estimator

Welfare changes by increments in γ_{42}^{INTER} show a different pattern from the case of risk aversion. Figure 6.14 illustrates changes of welfare associated with increases in γ_{42}^{INTER}. Though the effects are not globally monotonic (between no social learning (γ_{42}^{INTER} = 0.00) and γ_{42}^{INTER} = 0.25), the overall trend is fairly similar to results obtained from the aggregate model and the early adopter's model. The optimal value function $V^{INTER}\left(S^{INTER} \mid \Theta^{\gamma_{42}^{INTER}}\right)$ increases as γ_{42}^{INTER} rises up to 0.75, and then decreases beyond the social optimum γ_{42}^{INTER*} = 0.75. Increments in γ_{42}^{INTER} decelerate the adoption of GM technology as is illustrated in Figure 6.11 and Figure 6.12. Note that there exist situations where farm welfare increases, as represented by regions up to the social optimum γ_{42}^{INTER*} = 0.75 in Figure 6.14. This result shows the intermediate adopter may benefit from information externalities up to social optimum by saving his/her cost of social learning. This result reflects that the intermediate adopter exhibits free-riding behaviors in the presence of information externalities. Beyond social optimum, farmers would be willing to pay a positive amount of money as they are made worse off. Note that farmers' actual social learning, represented as the minimum distance estimator $\tilde{\gamma}_{42}^{INTER}$ = 0.94, occurs near the social optimum point for intermediate adopters.

Figure 6.14: Welfare Measures for GM Technology Adoption by Changes in the Social Learning Parameter for the Intermediate Adopter



According to Table 6.14, the intermediate adopter would be willing to pay only 0.38% of his/her present value of future payoffs to internalize information externalities in GM adoption.

Recall that social optimum was found consistent with the representative farmer's actual social learning (as $\gamma_{42}^{*} = \tilde{\gamma}_{42}$ = 0.80 in the aggregate model). Compared with the aggregate model, the intermediate adopter may adopt GM technology slightly inefficiently by generating an estimated loss of 0.38% from his/her payoffs. However, this loss implies a relatively small welfare cost. This indicates that intermediate adopters are reasonably efficient in relying on social learning and that they come close to internalizing information externalities in GM adoption.

Table 6.13: Welfare Measures and Costs of Social Learning for the Intermediate Adopter

Social Learning for GM Technology	The Optimal Value Function [a/]	Absolute Cost of Social Learning [b/]	Relative Cost of Social Learning (percent)
γ_{42}^{INTER}	$V^{l}\left(S^{l} \mid \Theta^{\gamma_{42}^{l}}\right)$	$C_{social-learning}^{INTER}$	$\bar{C}_{social-learning}^{INTER}$
0.00	41.80	3.23	7.74%
0.15	41.54	3.50	8.42%
0.25	41.63	3.41	8.18%
0.35	42.60	2.43	5.71%
0.45	43.48	1.56	3.58%
0.55	44.25	0.78	1.77%
0.65	44.78	0.25	0.56%
0.75 [c/]	45.04 [c/]	0.00 [c/]	0.00% [c/]
0.94 [d/]	44.87 [d/]	0.17 [d/]	0.38% [d/]
1.05	44.50	0.54	1.21%
1.15	44.07	0.97	2.19%
1.25	43.59	1.45	3.32%
1.35	43.08	1.95	4.53%

Note: $l = \{INTER\}$

[a/] [b/] Unit - $ hundred / acre

[c/] Social optimum γ_{42}^{INTER*}

[d/] The baseline case at the minimum distance estimator $\tilde{\gamma}_{42}^{INTER*}$

6.3.Late Adopter

6.3.1. Parameter Estimates and Adoption Curve

Given constants β_{11}^{LATE}, β_{22}^{LATE}, and γ_{31}^{LATE}, results of the late adopter's model estimation are presented in Table 6.15.

Table 6.14: Parameter Estimates of the Late Adopter's GM Adoption Model

Parameter	Implication	Estimate
Reward Function		
r^{LATE}	The Arrow-Pratt measure of absolute risk-aversion coefficient	1.34
$\overline{r}^{LATE}$	The Arrow-Pratt measure of relative risk-aversion coefficient	5.36
System Equation		
β_{11}^{LATE} a/	The effect of adoption of conventional technology on the average change in $\pi^{CONV,LATE}$	0.11
β_{22}^{LATE} b/	The effect of adoption of GM technology on the average change in $\pi^{GM,LATE}$	2.50
Measurement Equation		
γ_{11}^{LATE}	The effect of individual learning for conventional technology	0.65
γ_{21}^{LATE}	The effect of social learning for conventional technology	0.51
γ_{31}^{LATE} c/	The effect of yield for GM seed to $\pi^{CONV,LATE}$	1.12
γ_{32}^{LATE}	The effect of individual learning for GM technology	1.28
γ_{42}^{LATE}	The effect of social learning for GM technology	1.03

Note: Goodness of fit is 0.0340.

a/ b/ c/ Given from $\tilde{\beta}_{11}^{INTER}$, $\tilde{\beta}_{22}^{INTER}$, and $\tilde{\gamma}_{31}^{INTER}$

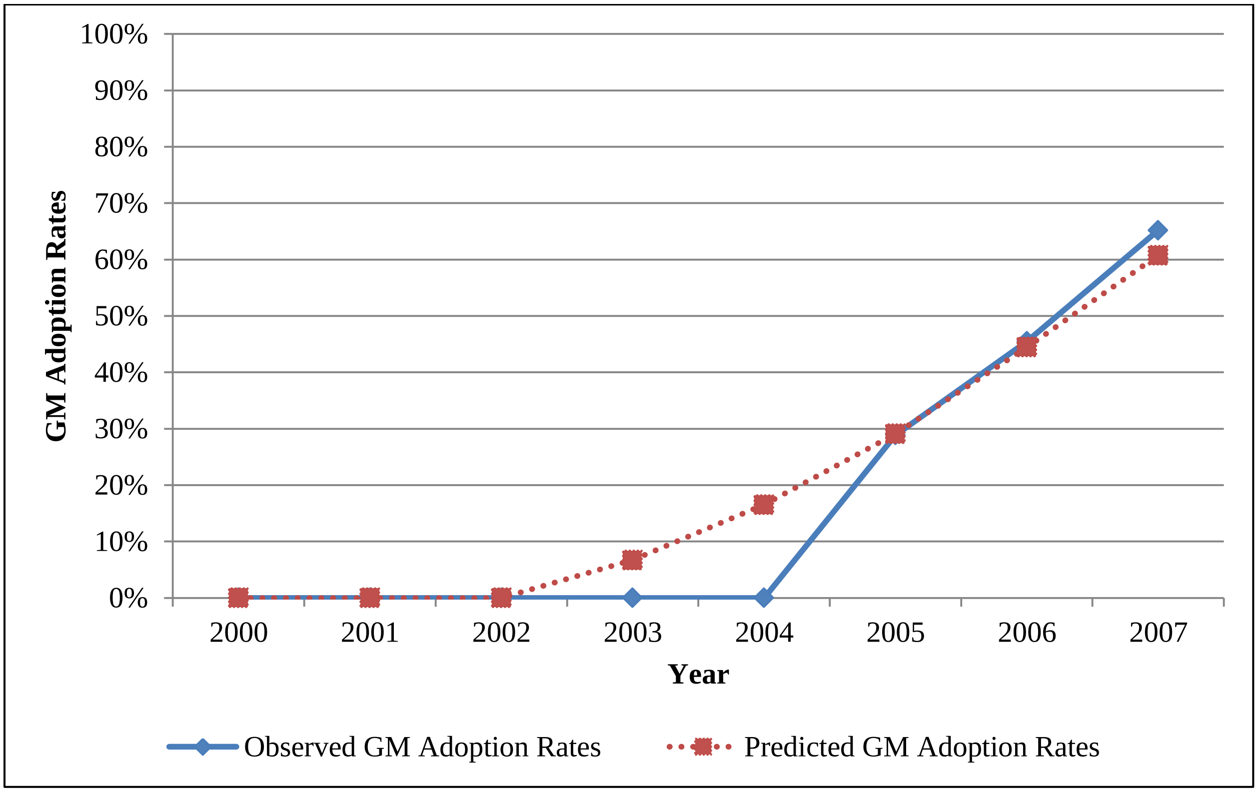
The late adopter's absolute risk aversion coefficient is 1.34 with its corresponding relative risk aversion coefficient $\overline{r}^{LATE}$ being 5.36.[34] This shows the late adopter exhibits a high level of risk aversion as $\overline{r}^{LATE}$ is greater than 5 (Gollier, 2001, p. 31). All the parameters in the measurement equation γ^{LATE}'s are estimated to be positive, indicating that both individual and social learning

[34] The selected late adopter's expected total profit during the analysis period is estimated as $4.00 million.

improve the profitability for each technology. Like other models, the effects of individual learning are estimated to be higher than the effects of social learning, $\gamma_{11}^{LATE} > \gamma_{21}^{LATE}$ for conventional seed and $\gamma_{32}^{LATE} > \gamma_{42}^{LATE}$ for GM seed. Compared with the early- and the intermediate- adopter's models, the social learning parameter γ_{42}^{LATE} is estimated to be largest among parameters γ_{42}^{l}'s across l-type models.

The goodness-of-fit is calculated to be 0.0340, showing the late adopter's DP model fits the selected late adopter's GM adoption pattern very well. Figure 6.15 provides comparison between the observed and simulated adoption rates from the late adopter's DP model.

Figure 6.15: Observed and Predicted GM Adoption Rates for the Late Adopter, 2000-2007



Note: GM adoption rates are percentage of planted acres to GM seed.

Also, Table 6.16 provides specific values concerning adoption rates. Except for adoption rates in 2003 and 2004, the overall estimation results fit the data quite well.

Table 6.15: Observed and Predicted GM Adoption Rates for the Late Adopter, 2000-2007

Year	Observed GM Adoption Rates[a/]	Predicted GM Adoption Rates[b/]	Squared Residual[c/]
2000	0.00%	0.00%	0.0000
2001	0.00%	0.00%	0.0000
2002	0.00%	0.00%	0.0000
2003	0.00%	6.73%	0.0045
2004	0.00%	16.53%	0.0273
2005	28.86%	29.09%	0.0000
2006	45.49%	44.45%	0.0001
2007	65.20%	60.76%	0.0020
Sum of Squared Residuals (Goodness-of-fit statistic)			0.0340

Note: [a/] [b/] GM adoption rates are percentage of planted acres to GM seed.
[c/] Squared residual c/ = $(a/ – b/)^2$

6.3.2. Hypothesis Testing

We focus on the role of risk aversion and the social learning parameter in GM technology adoption. For the late adopter's DP model, all the relevant null hypotheses are rejected at the 1% level (Scenario 1, Scenario 3, Scenario 5, and Scenario 6) or at the 5% level (Scenario 2 and Scenario 4).

The null hypothesis of risk neutrality $H_0 : r^{LATE} = 0$ is rejected at the 1% level, indicating the late adopter's risk preferences exhibit risk aversion with strong statistical significance. For the social learning parameter γ_{42}^{LATE}, the rejection of null hypothesis $H_0 : \gamma_{42}^{LATE} = 0$ provides the econometric evidence that social learning plays a key role and affects the adoption of GM technology.

Table 6.16: Results of Hypothesis Testing across Scenarios for the Late Adopter

Scenario sc	Null Hypothesis	SSR(Θ^l)[a/]	SSR($\Theta_*^{l,sc}$)[b/]	df1[c/]	df2[d/]	F ^{sc} (df1, df2)[e/]
1	$H_0: r^{LATE} = 0$	0.0340	0.5849	1	3	48.68***
2	$H_0: \gamma_{21}^{LATE} = 0$	0.0340	0.3868	1	3	31.18**
3	$H_0: \gamma_{42}^{LATE} = 0$	0.0340	5.9243	1	3	520.48***
4	$H_0: \gamma_{21}^{LATE} = 0 \,\&\, \gamma_{42}^{LATE} = 0$	0.0340	0.7153	2	3	30.10**
5	$H_0: \gamma_{21}^{LATE} = \gamma_{42}^{LATE} = 0.51$	0.0340	1.6129	2	3	69.76***
6	$H_0: \gamma_{21}^{LATE} = \gamma_{42}^{LATE} = 1.03$	0.0340	3.3396	2	3	146.05***

Note: Statistical significance is denoted as *** at the 1% level, ** at the 5% level, and * at the 10% level.

[a/]: Goodness-of-fit statistic under Θ^l , $l = \{LATE\}$

[b/]: Goodness-of-fit statistic under $\Theta_*^{l,sc}$, $l = \{LATE\}$

[c/]: Degrees of freedom for the numerator

[d/]: Degrees of freedom for the denominator

[e/]: F-statistic

6.3.3. Sensitivity Analysis on Adoption Path

Following the hypothesis testing, sensitivity analysis is conducted to investigate how GM technology adoption pattern changes with risk aversion or the strength of the social learning parameter. Figure 6.16 illustrates how the late adopter's simulated GM adoption curves change with the level of risk aversion r^{LATE}. The benchmark case simulated at the minimum distance estimator is drawn as a dashed line. At the lower level of r^{LATE}, changes in GM adoption rates are ambiguous. The overall trend shows small upward movements at low levels of r^{LATE}, reflecting the potential role of portfolio selection. But the adoption rates decrease as r^{LATE} increases at higher level of $r^{LATE} > 1.50$.

Figure 6.16: Simulation of the GM Technology Adoption by Changes in Risk Aversion for the Late Adopter

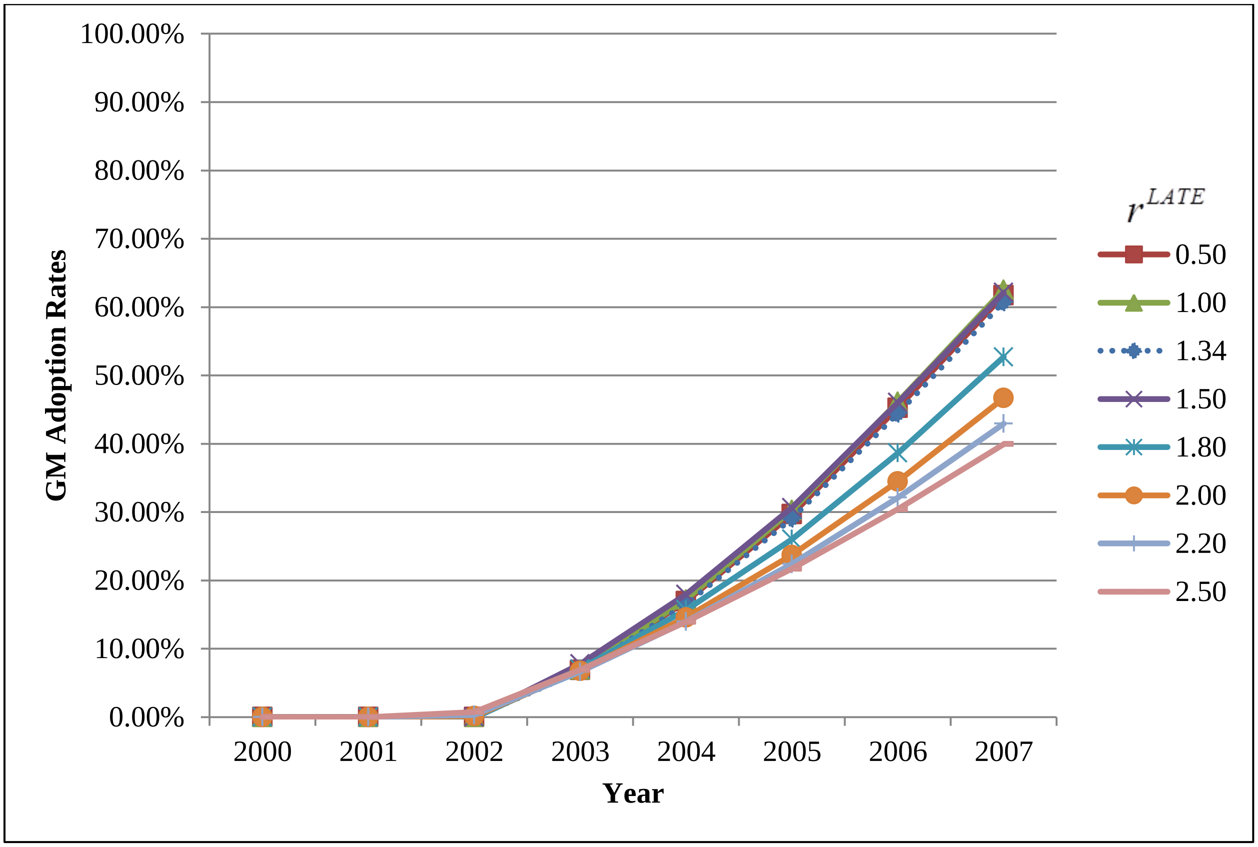
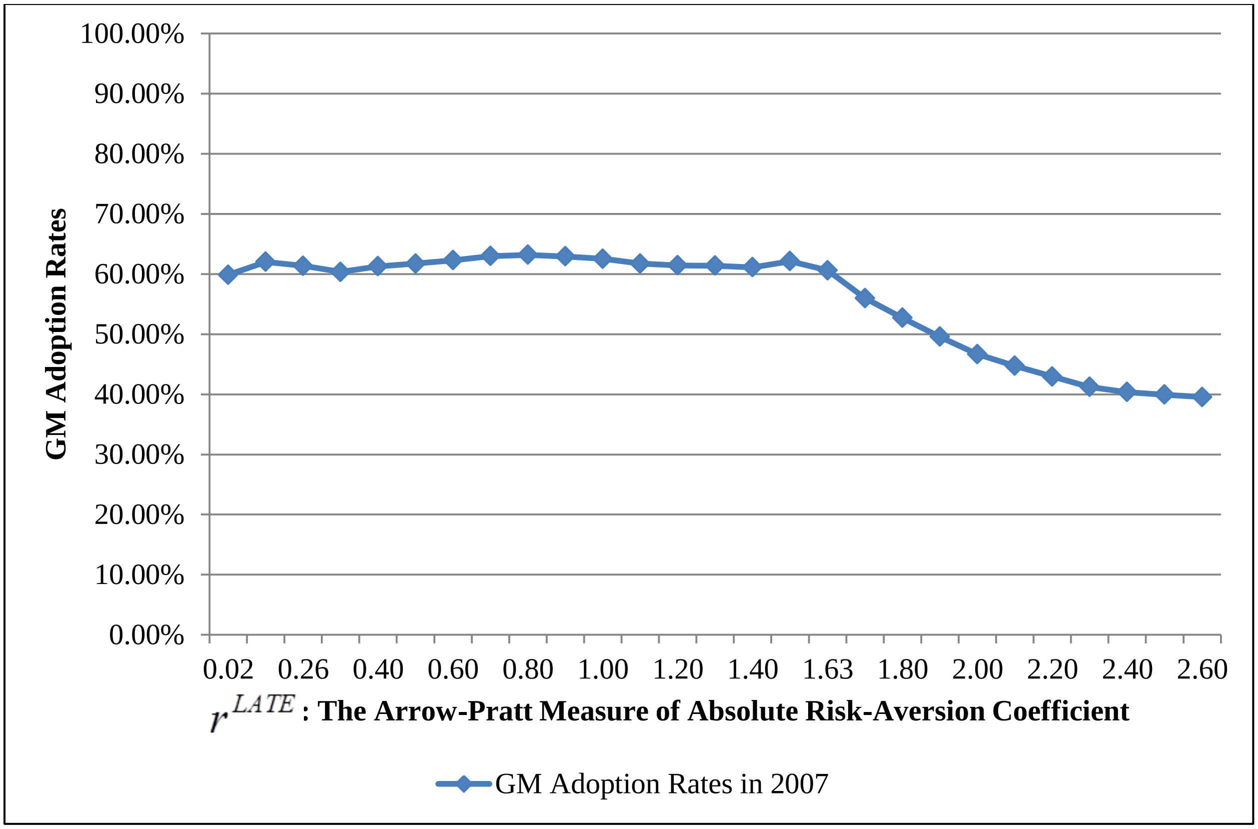


Table 6.17: Simulations of GM Technology Adoption by Changes in Risk Aversion for the Late Adopter

Risk Aversion	**Simulated GM Adoption Rates for the Early Adopter**								**Goodness-of-fit**
r^{LATE}	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	
0.50	0%	0%	0%	6.92%	16.96%	29.70%	45.27%	61.74%	0.04
1.00	0%	0%	0%	6.96%	17.22%	30.29%	46.14%	62.55%	0.04
1.34	0%	0%	0%	6.73%	16.53%	29.09%	44.45%	60.76%	0.03
1.50	0%	0%	0%	7.79%	17.97%	30.66%	46.04%	62.15%	0.05
1.80	0%	0%	0%	7.05%	15.70%	26.05%	38.63%	52.70%	0.06
2.00	0%	0%	0.14%	6.77%	14.58%	23.73%	34.50%	46.69%	0.08
2.20	0%	0%	0.30%	6.64%	13.99%	22.41%	32.13%	42.94%	0.10
2.50	0%	0%	0.76%	6.93%	13.93%	21.71%	30.43%	39.95%	0.12

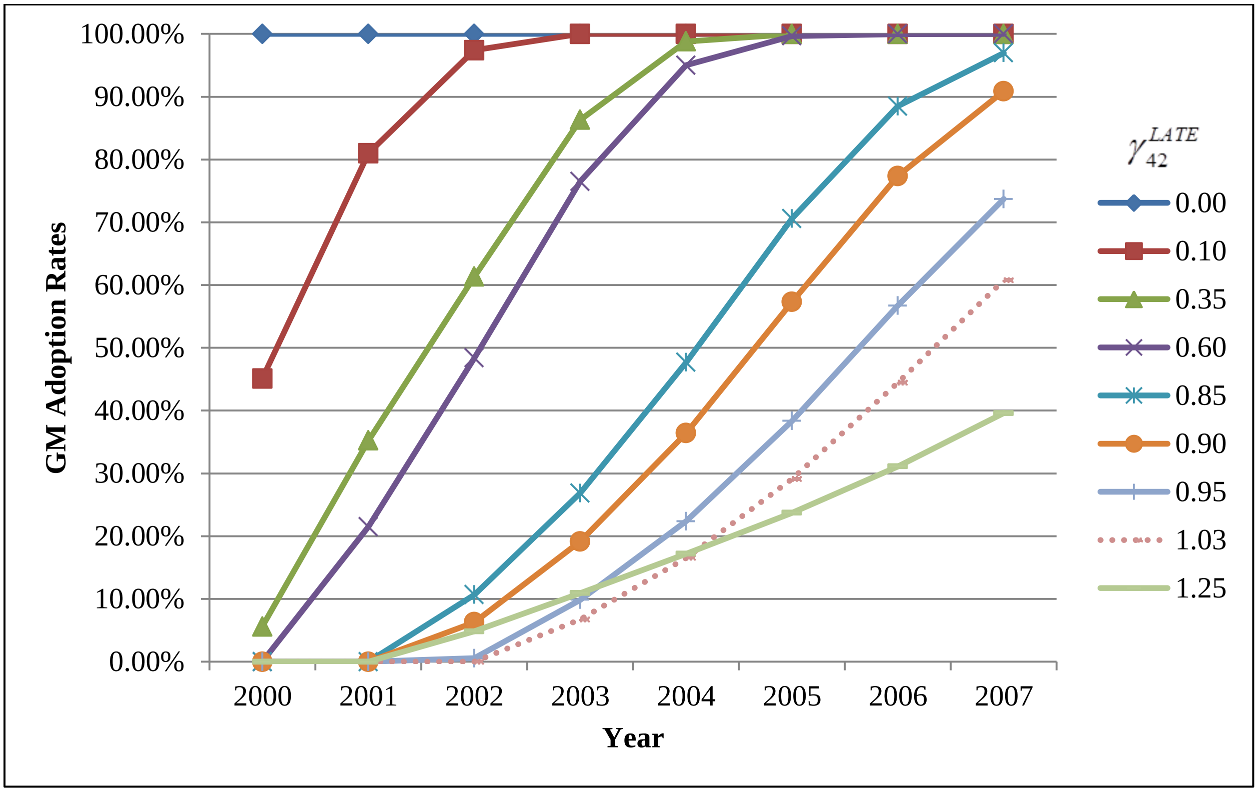
Figure 6.17 illustrates changes of simulated adoption rates in 2007. For the late adopter, the overall changes of adoption rates are somewhat similar to the trend shown in the intermediate adopter's DP model.

Figure 6.17: Simulated GM Adoption Rates in 2007 by Changes in Risk Aversion for the Late Adopter



While changes of simulated adoption rates are non-monotonic by changes in risk aversion, the movements of GM adoption curve show obvious decreasing monotonicity with respect to the social learning parameter γ_{42}^{LATE}. With the benchmark case drawn as a dashed line, Figure 6.18 illustrates how the speed of GM technology adoption is affected by changes in γ_{42}^{LATE}.

Figure 6.18: Simulation of the GM Technology Adoption by Changes in the Social Learning Parameter for the Late Adopter

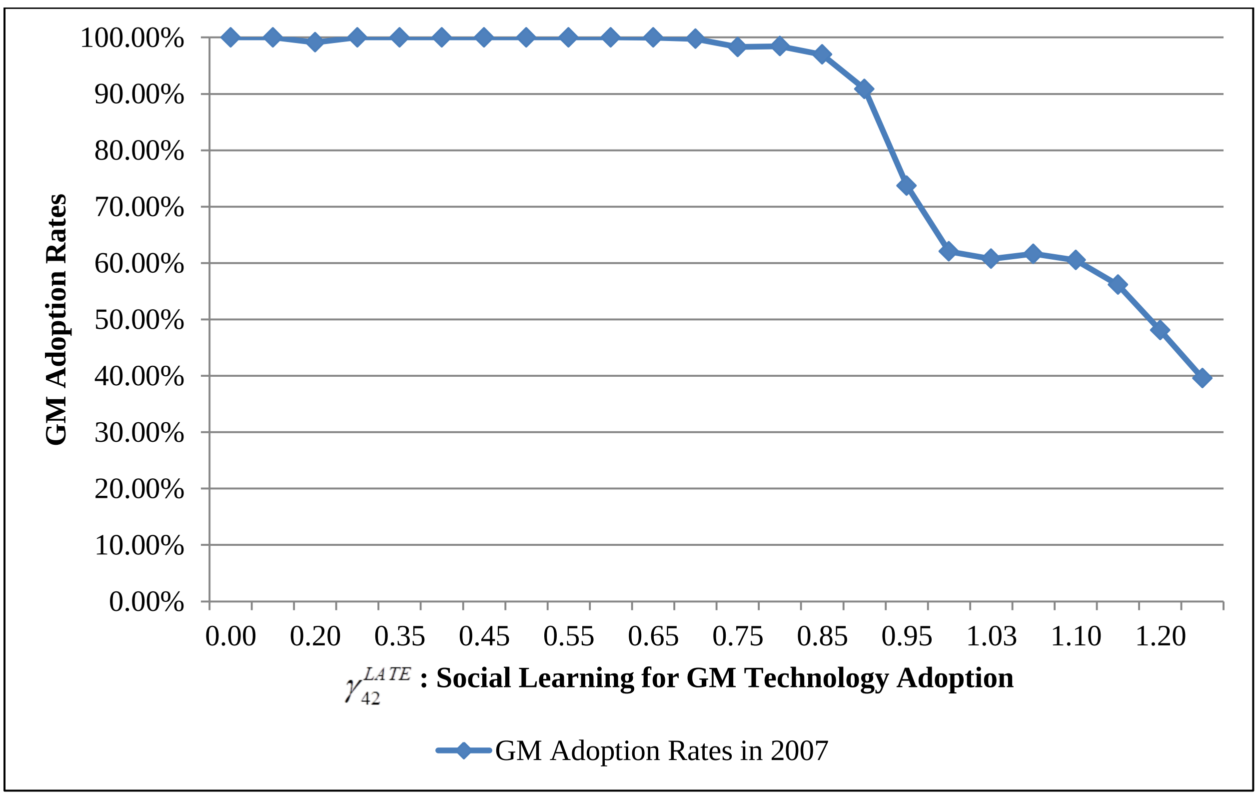


Starting from a counterfactual case of no social learning ($\gamma_{42}^{LATE} = 0$), GM adoption curves shift downwards in the late adopter's DP model. This result indicates the late adopter has an incentive to delay GM adoption. As γ_{42}^{LATE} rises, the late adopter relies more on social learning and has a stronger incentive to delay his/her GM adoption, waiting for his/her neighbors to adopt so that it can benefit from the information externality. Table 6.19 provides specific values, and Figure 6.19 illustrates how the simulated adoption rates of GM technology change in 2007 as γ_{42}^{LATE} changes.

Table 6.18: Simulation of the GM Technology Adoption by Changes in the Social Learning Parameter for the Late Adopter

Social Learning	Simulated GM Adoption Rates for the Early Adopter								Goodness-of-fit
γ_{42}^{LATE}	2000	2001	2002	2003	2004	2005	2006	2007	
0.00	100%	100%	100%	100%	100%	100%	100%	100%	5.92
0.10	45.10%	80.99%	97.42%	100%	100%	100%	100%	100%	4.73
0.35	5.61%	35.24%	61.34%	86.33%	98.81%	99.99%	100%	100%	3.15
0.60	0.00%	21.50%	48.40%	76.50%	95.01%	99.68%	100%	100%	2.69
0.85	0.00%	0.00%	10.67%	26.85%	47.69%	70.60%	88.48%	96.97%	0.78
0.90	0.00%	0.00%	6.30%	19.16%	36.41%	57.32%	77.39%	90.87%	0.43
0.95	0.00%	0.00%	0.56%	9.86%	22.37%	38.35%	56.74%	73.72%	0.10
1.03	0.00%	0.00%	0.00%	6.73%	16.53%	29.09%	44.45%	60.76%	0.04
1.25	0.00%	0.00%	4.83%	10.92%	17.20%	23.72%	31.10%	39.59%	0.13

Figure 6.19: Simulated GM Adoption Rates in 2007 by Changes in the Social Learning Parameter for the Late Adopter



As shown in the previous sections, results from the late adopter's DP model provide strong evidence of information externalities. Farmers delay their GM technology adoption as γ_{42}^{LATE} increases, reflecting that late adopters free ride on the information provided by their neighbors.

6.3.4. Welfare Analysis

As is illustrated in Figure 6.20, the late adopter's simulated optimal value functions are monotonically decreasing as the level of risk aversion r^{LATE} increases.

Figure 6.20: Welfare Measures for GM Technology Adoption by Changes in Risk Aversion for the Late Adopter

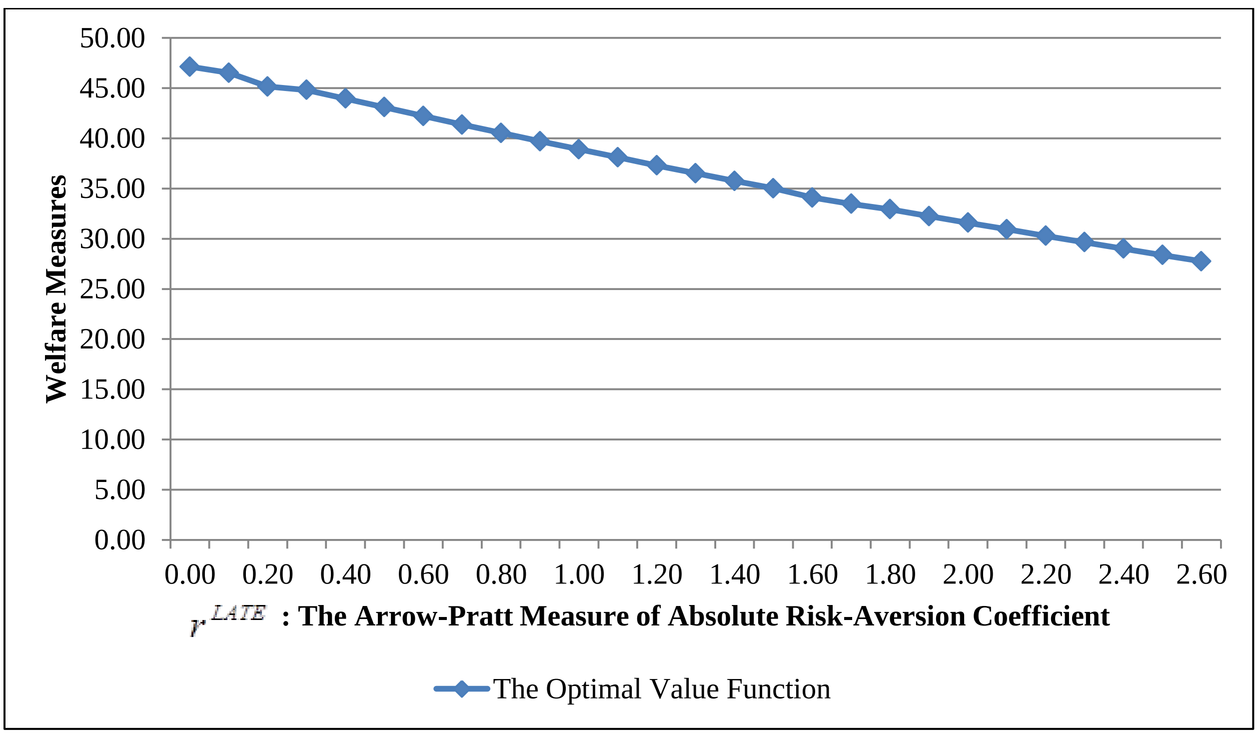


Table 6.20 provides the associated relative cost of risk aversion $\bar{C}^{LATE}_{risk-aversion}$. We can compare $\bar{C}^{l}_{risk-aversion}$ for $l = \{EARLY, INTER\}$ with the baseline case of each farm type's simulation using the minimum distance estimator. The late adopter's relative cost of risk aversion is found to be relatively high ($\bar{C}^{EARLY}_{risk-aversion}$ = 6.90% in Table 6.6, $\bar{C}^{INTER}_{risk-aversion}$ = 6.05% in Table 6.13, and $\bar{C}^{LATE}_{risk-aversion}$ = 30.19% in Table 6.20). This result reflects that late adopters exhibit stronger aversion to risk than early or intermediate adopters. This documents heterogeneity in risk preferences across farm types.

Table 6.19: Welfare Measures and Costs of Risk Aversion for the Late Adopter

Risk Aversion (Absolute)	The Optimal Value Function[a]	Absolute Cost of Risk Aversion[b]	Relative Cost of Risk Aversion (percent)
r^{LATE}	$V^{l}\left(S^{l} \mid \Theta^{r^{l}}\right)$	$C^{LATE}_{risk-aversion}$	$\bar{C}^{LATE}_{risk-aversion}$
0.00	47.13	0.00	0.00%
0.50	43.10	4.03	9.35%
1.00	38.91	8.23	21.15%
1.34[c]	36.20[c]	10.93[c]	30.19%[c]
1.50	35.02	12.12	34.61%
2.00	31.59	15.54	49.20%
2.50	28.38	18.76	66.09%

Note: $l = \{LATE\}$

[a] [b] Unit - \$ hundred / acre

[c] The baseline case at the minimum distance estimator

In the late adopter's DP model, the effects of the social learning parameter γ^{LATE}_{42} show a similar pattern as other farm type models. As is illustrated in Figure 6.21, the late adopter can increase his/her welfare measures by delaying the adoption of GM seed as the strength of information externalities represented by γ^{LATE}_{42} increases.

Figure 6.21: Welfare Measures for GM Technology Adoption by Changes in the Social Learning Parameter for the Late Adopter

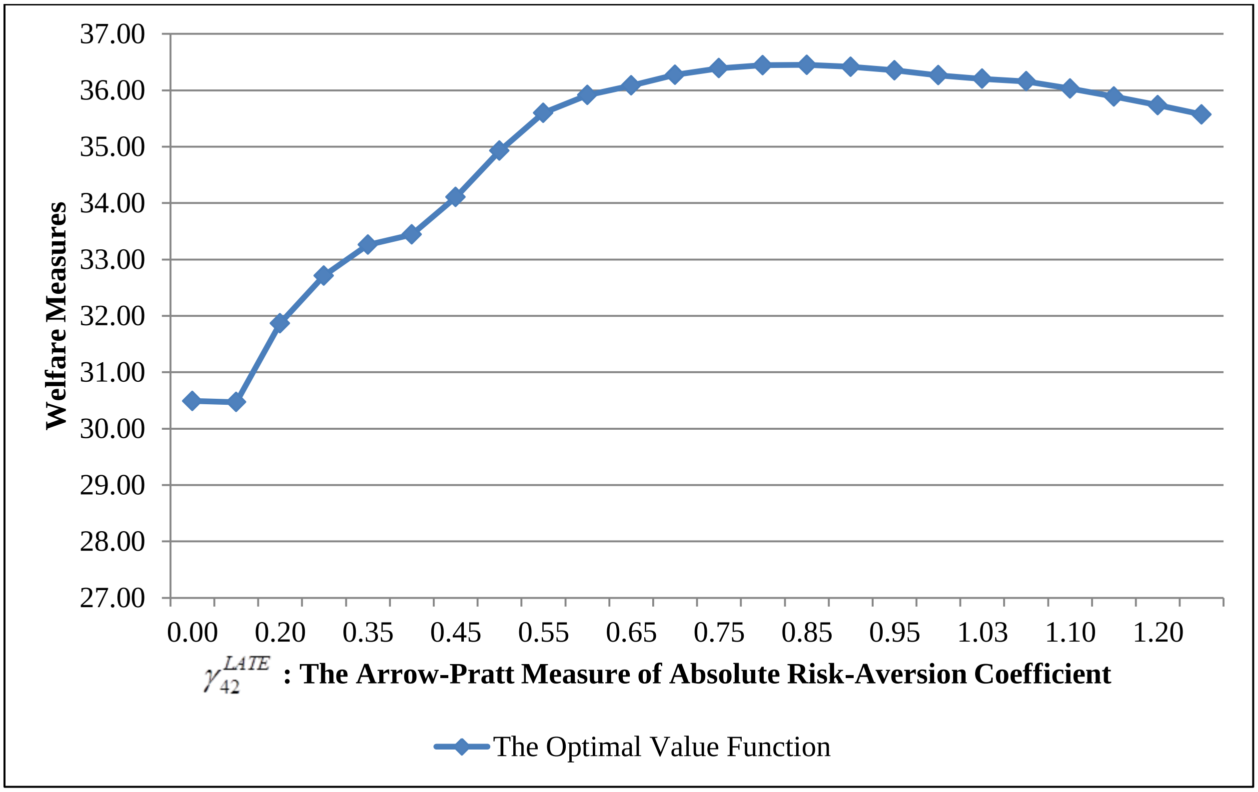


Table 6.20: Welfare Measures and Costs of Social Learning for the Late Adopter

Social Learning for GM Technology	The Optimal Value Function [a/]	Absolute Cost of Social Learning [b/]	Relative Cost of Social Learning (percent)
γ_{42}^{LATE}	$V^l\left(S^l \mid \Theta^{\gamma_{42}^l}\right)$	$C_{social-learning}^{LATE}$	$\bar{C}_{social-learning}^{LATE}$
0.00	30.49	5.96	19.54%
0.20	31.87	4.58	14.38%
0.45	34.10	2.35	6.88%
0.65	36.09	0.36	1.01%
0.85[c/]	36.45[c/]	0.00[c/]	0.00%[c/]
1.03[d/]	36.20[d/]	0.25[d/]	0.68%[d/]
1.15	35.89	0.56	1.56%

Note: $l = \{LATE\}$

[a/] [b/] Unit - \$ hundred / acre

[c/] Social optimum γ_{42}^{LATE*}

[d/] The baseline case at the minimum distance estimator $\tilde{\gamma}_{42}^{LATE}$

The late adopter's estimated social learning occurs at the level of $\tilde{\gamma}_{42}^{LATE}$ = 1.03 (as given by the minimum distance estimate), which is slightly higher than his/her social optimum γ_{42}^{LATE*}. We find that the late adopter would be willing to pay 0.68% of his/her present value of future payoffs to obtain the optimum social learning. This is a relatively small welfare effect. Thus, actual social learning seems close to the social optimum, indicating that the late adopter is reasonably efficient at internalizing the information externalities in GM adoption.

6.4.Comparison of the Disaggregate Adoption Models by Farm Type

The aggregate model and the l-type adopter's disaggregate model for l = {$EARLY$, $INTER$, $LATE$} assume farmers' optimal policy functions are the same within each group. But by allowing parameters to change across groups, each l-type adopter's DP model introduces the potential for farm heterogeneity that was neglected in the aggregate model. Such heterogeneity is captured by differentiating parameters in the DP system across l-type models. Thus, comparing parameters Θ^l across l-type farmers provides evidence on how farmers differ across farm groups (classified as early, intermediate, and late adopters) and how these differences affect adoption patterns and welfare.

Heterogeneity in parameters is examined with a focus on the degrees of risk aversion r^l and the extent of social learning for GM technology γ_{42}^l for each farm type l = {$EARLY$, $INTER$, $LATE$}. Table 6.22 summarizes estimated parameters for each l-type adopter's disaggregate model. For the benchmark case, the estimation results from the aggregate model are also reported, denoted by $l = \{AGG\}$ hereafter. Differences in a specific parameter across l-groups provide information on the nature of farmers' heterogeneity and their implications for GM adoption.

Table 6.21: Parameter Estimates across the Disaggregate Adoption Models

Parameter	Implication	EARLY	INTER	LATE	AGG
Reward Function					
r^l	The Arrow-Pratt measure of absolute risk-aversion coefficient	0.08	0.35	1.34	0.54
$\bar{r}^{l}$ [a/]	The Arrow-Pratt measure of relative risk-aversion coefficient	0.69	2.91	5.36	4.12
System Equation					
β_{11}^{l} [b/]	The effect of adoption of conventional technology on the average change in $\pi^{CONV,l}$	0.11	0.11	0.11	2.20
β_{22}^{l} [c/]	The effect of adoption of GM technology on the average change in $\pi^{GM,l}$	2.50	2.50	2.50	2.50
Measurement Equation					
γ_{11}^{l}	The effect of individual learning for conventional technology	1.26	0.72	0.65	1.21
γ_{21}^{l}	The effect of social learning for conventional technology	0.85	0.55	0.51	1.01
γ_{31}^{l} [d/]	The effect of yield for GM seed to $\pi^{CONV,l}$	1.12	1.12	1.12	1.25
γ_{32}^{l}	The effect of individual learning for GM technology	1.52	1.35	1.28	1.80
γ_{42}^{l}	The effect of social learning for GM technology	0.17	0.94	1.03	0.80
Goodness-of-fit		0.0059	0.0523	0.0340	0.0303

Note: $l = \{EARLY, INTER, LATE\}$ indicates farm type at the disaggregate models, where $EARLY$, $INTER$, and $LATE$ stand for the early-, the intermediate-, and the late- adopter, respectively. AGG indicates a representative farmer at the aggregate adoption model.

[a/] $\bar{r}^l = r \times$(expected total profit for l-farmer). The expected total profit estimates are $8.59 million for the early adopter, $8.32 million for the intermediate adopter, $4 million for the late adopter, and $7.63 million for the representative farmer at the aggregate model.

[b/ c/ d/] Parameter estimates from the late adopter's DP model are used as given constants in the early- and the late-adopter's DP models. $\tilde{\beta}_{11}^{INTER} = \beta_{11}^{EARLY} = \beta_{11}^{LATE}$, $\tilde{\beta}_{22}^{INTER} = \beta_{22}^{EARLY} = \beta_{22}^{LATE}$, and $\tilde{\gamma}_{31}^{INTER} = \gamma_{31}^{EARLY} = \gamma_{31}^{LATE}$.

Being a unit-free measurement, the Arrow-Pratt measure of relative risk-aversion coefficient $\bar{r}^l$ is used for evaluating risk aversion for each farm type. $\bar{r}^l$ is found to affect GM technology adoption. As discussed above, a higher degree of risk aversion often (but not always) contributes to slowing down adoption rates. Importantly, the degree of risk aversion also varies across farm types. In the late adopter's model, $\bar{r}^{LATE}$ is the largest as 5.36, followed by the intermediate adopter's $\bar{r}^{INTER}$ = 2.91 and the early adopter's $\bar{r}^{EARLY}$ = 0.69. Following Gollier (2001, p.31), the late adopter exhibits a high level of risk aversion as $\bar{r}^{LATE}$ > 5, and the early adopter exhibits a low level of risk aversion as $\bar{r}^{EARLY}$ < 1. The intermediate adopter exhibits a medium level of risk aversion by 1 < $\bar{r}^{INTER}$ < 5.

Thus, we find evidence of heterogeneity in risk preferences across farm types. According to the adoption timing or adoption pattern, the late adopter is featured to exhibit relatively higher level of risk aversion ($\bar{r}^{l}$ > 5), and the early adopter is featured to exhibit relatively lower level of risk aversion ($\bar{r}^{l}$ < 1). The intermediate adopter's risk aversion may be between those two extreme points with the degree of medium level (1 < $\bar{r}^{l}$ < 5). Finding a monotonic relationship between risk aversion and adoption timing seems important. The more risk-averse a farmer is, the later he/she would adopt a new technology (GM seeds). This is consistent with findings from the previous literature such as Liu (2008).

The sensitivity analysis in terms of r^{l} in the aggregate model shows that the speed of GM technology adoption is faster up to some level of r^{l} (r < 2.20 in the aggregate model) and slower beyond that level, reflecting the presence of farmers' diversification strategy. This trend appears to be present in the intermediate- and the late- adopter's DP model, but not in the early adopter's model. Though direct comparison across the disaggregate models is not available, a qualitative comparison of the effects of risk preferences across farm types is instructive. While the early adopter doesn't seem to exhibit diversification patterns associated with portfolio selection, the intermediate- and the late- adopter do show patterns of diversification in their adoption choices between conventional and GM seeds.

The social learning parameter for GM technology γ_{42}^{l} represents the strength of information externalities. Information externalities are shown to slow down the speed of GM technology adoption, impeding its diffusion. That is, the larger the social learning parameter γ_{42}^{l}, the later a farmer would adopt GM technology. This relation reflects farmers' free-riding behaviors in the presence of information externalities. Table 6.22 suggests a monotonic relationship between γ_{42}^{l} and adoption timing across l-farm types. Importantly, the extent of reliance on external information also seems to vary across farm types. Estimated γ_{42}^{l}'s are shown to be highest for the late adopter (γ_{42}^{LATE} = 1.03), followed by the intermediate adopter (γ_{42}^{INTER} = 0.94) and the early adopter (γ_{42}^{EARLY} = 0.17). This reflects that farmers relying more on social interactions tend to be late adopter. That is, the higher the strength of information externalities is (or the more social interaction is), the later farmers would adopt GM technology.

As discussed in the previous sections, the changes in γ_{42}^{l} affect farmers' adoption behaviors in two different ways. First, it affects the speed of GM technology adoption: increasing level of information externalities γ_{42}^{l} slows down adoption by providing farmers incentives to wait for information for their adopting neighbors. Second, increasing γ_{42}^{l} makes farmers better off up to some level of γ_{42}^{l} (social optimum), where famers can save the cost of individual learning by free riding on their neighbors. Alternatively, excessive social learning can occur and make farmers worse off if social learning goes beyond its social optimum, implying that free-riding would be socially inefficient.

Our analysis shows the incremental effects of γ_{42}^{l} across l-type models. It finds some small degree of inefficiency in γ_{42}^{l} around its social optimum across l-type adopters. This can be seen by looking at the relative cost of social learning across l-type DP models. Compared to zero cost at the social optimum, the early adopter would pay 0.16% of his/her welfare before social optimum (Table 6.7), the intermediate adopter would pay 0.38% of his/her welfare beyond social optimum (Table 6.14), and the late adopter would pay 0.68% of his/her welfare beyond social optimum (Table 6.21). This indicates that the later farmers adopt GM seeds, the more inefficiently they internalize information externalities. That is, laggards are less effective in capturing the benefits from social learning. Finally, note that, while non-zero, these welfare effects are relatively small. This indicates that, while there is heterogeneity in the reliance on social learning across farm types, farmers within each type may be reasonably efficient in managing the information externalities they obtain from their neighbors.

Chapter 7 : Conclusion

7.1.Summary & Conclusion

This dissertation has analyzed the behaviors of U.S. corn farmers and their decisions to adopt Genetically Modified (GM) technology. The investigation has been done in a dynamic context, with a focus on risk and learning effects. We consider farmers' risk preferences and their individual and social learning as key determinants affecting the adoption of GM technology. We analyze the role of risk and risk aversion in farmers' adoption decisions and highlight the relative roles of individual learning and social learning, identifying how they affect GM technology adoption.

For this research, we develop a conceptual structural dynamic programming (DP) model capturing both individual and social learning and risk preferences in a parameterized structure. Assuming both conventional and GM technologies are risky choices with uncertain profitability, we consider that forward-looking farmers make adoption decisions of how many acres to plant using conventional seed and GM seed so as to maximize their present value of all future payoffs, with the learning process as underlying dynamics. Then, farmers' learning process implies updating their information about the uncertain profitability for each technology. Acquired information by farmers is represented by their subjective beliefs given by the mean and variance of the distribution of uncertain profitability.

Each year, farmers decide whether or not to adopt GM technology and how many acres to plant in GM seeds. The choices between conventional technology and GM technology are made at planting time before actual profits are known. Thus, our DP problem involves imperfect state information as the state variables (profits) are unobservable. This is handled by adding measurement equations, which provide information about related variables correlated with profits and allow an updating of the assessed distribution of profit for each technology. In the measurement equations, farmers' previous year's yield information for each technology is used to capture individual learning as it represents farmers' own experience about the profitability for each technology. Similarly, neighboring farmers' adoption rates for each technology are used to capture social learning. That is, farmers' learning processes are parameterized in terms of individual learning and social learning. The degrees of individual learning and social learning for each technology (conventional seed and GM seed) are thus represented by specific parameters. In this context, the social learning parameter reflects the strength of information externalities in adoption decisions.

Our DP model under imperfect state information is given by Bellman equation where sufficient statistics are used under the assumption of normality on the distribution of profit. Under normality, sufficient statistics reduce to the mean and the variance of the distribution. In terms of learning, the evolution of mean and variance is given by the Kalman filter, which provides a convenient parameterized structure for updating mean and variance given new observations. Through parameters in the measurement equations, it also provides a basis to examine the relative roles of individual learning and social learning. That is, Bellman equation with sufficient statistics is specified under normal distribution.

Under the expected utility model, we represent risk preferences by an additive mean-variance utility function. This is consistent with the assumptions of normal distribution and Constant Absolute Risk Aversion (CARA). Then, the reward function includes the Arrow-Pratt measure of absolute risk aversion coefficient in its functional form. In addition, under stationarity, the relevant Bellman equation is a time-invariant functional equation whose unknowns are its value function. Then, Bellman equation can be numerically solved using the collocation method. In our paper, dynamic optimization is combined with parameter estimation. An algorithm is devised so that dynamic optimization is nested within a minimum distance estimator procedure.

Then, we apply Bellman equation with the Kalman filter to the DMR panel dataset. The data is composed of 136 corn farmers in and around the U.S. Corn Belt. Considering heterogeneity across farmers, we develop four models of farmers' adoption pattern. The first model is for a representative farmer, i.e. a farmer that represents aggregate behavior, whose economic variables are at average levels of the whole group. It is used as a benchmark case and covers the whole DMR panel dataset. The other models are for disaggregate models applied to three sub-groups of farmers classified by farm type in terms of adoption timing: the early- , the intermediate-, and the late- adopters of GM technology. This classification allows for heterogeneity in parameters across groups, which are independent to initial conditions.

For each type of DP model, we identify and estimate parameters using a minimum distance estimator. Our results show that the risk-aversion coefficient in the reward function and all learning parameters in the measurement equation are estimated to be positive, indicating farmers are risk-averse, and both individual and social learning play roles in GM technology adoption. Especially, the effects of individual learning on adoption are shown to be greater than the effects of social learning for each technology. This is consistent with findings from previous literature demonstrating a new technology is adopted more effectively through individual learning than through social learning (Baerenklau, 2005; Conley and Udry, 2010; Munshi, 2004).

From the econometric viewpoints, hypothesis testing is implemented for selected parameters. Using an F-test, the null hypotheses of risk neutrality and of no social learning are rejected with high statistical significance, implying that risk aversion and social learning have significant impacts on adoption decisions. Sensitivity analysis of the effects of these parameters on adoption behavior is also implemented. Results provide important information: First, a higher level of risk aversion tends to reduce adoption rates (as farmers adopt later). However, there are also situations where increments in risk aversion increase the adoption of GM seed. These situations reflect that farmers exhibit behavior consistent with portfolio selection as diversification is used to reduce risk when both conventional seed and GM seed are risky choices. That is, our model captures farmers' diversification strategy by considering both new and old technologies are risky. Second, increases in the social learning parameter for GM technology impede the adoption of GM technology. This reflects the presence of information externalities in terms of free-riding behavior. Farmers have incentive to wait and delay their GM adoption in an attempt to learn more from their adopting neighbors. In sum, our paper provides evidence of the presence of information externalities and their impacts on GM technology adoption.

Welfare analysis shows that risk aversion makes farmers worse off. This is an expected result: risk-averse farmers are willing to pay to avoid risk. As the degree of risk aversion increases, the cost of risk (as measured by the willingness-to-pay to eliminate risk) also increases, and welfare declines. The impacts of the social learning parameters on welfare measures reflect the effects of information externalities. As noted above, increments in the social learning parameter slow down adoption rates. But the impact of information externalities on welfare can be either positive or negative. We find that actual social learning is close to social optimum, which implies that farmers are reasonably efficient at internalizing the information externalities in GM adoption.

Heterogeneity across farm type is investigated by comparing parameters across the disaggregate models. Results show two key features. First, relative risk aversion coefficient is higher for the late adopter and lower for the early adopter. This reflects that farmers' adoption timing is related to their degree of risk aversion: the more risk-averse farmers are, the later they adopt GM technology. Second, the social learning parameter, representing the strength of information externalities, is higher for the late adopter and lower for the early adopter, indicating that early adopters rely less on information externalities, while late adopters rely more on information from their neighbors. These different parameter estimates across models document the presence of heterogeneity in learning across farm types.

7.2.Contributions

To our knowledge, empirical analyses of joint roles of risk and learning on GM technology adoption are quite rare due to lack of available empirical data. Moreover, dynamic analysis using DP has been difficult to conduct because of inadequate good panel data in a relatively short history of GM technology. Thus, this dissertation makes the following contributions to the literature.

First, our research addresses the challenges of conducting an empirical analysis of unobservable factors on GM technology adoption – risk preferences and learning effects with information externalities. While observable farm characteristics such as farm size, credit constraints, and human resources have been investigated by the previous literature, the roles of learning are rarely highlighted due to lack of empirical data. Using an unique farm-level adoption data (the DMR data), our research provides a refined analysis of the role of individual learning versus social learning in technology adoption by relying on the Kalman filter for updating mean and variance, along with a parameterized structure representing the nature of the learning process. In addition, though risk and risk preferences have received lots of concerns by researchers, most of literature has counted on field experiments and survey data where establishing linkages between risk exposure and risk aversion is often difficult. However, our study investigates directly the impact of risk aversion on observed behavior by parameterizing risk aversion coefficient in the structural model. In short, our research contributes in providing empirical analysis of risk preferences and individual/social learning in the GM technology adoption literature remaining few.

Second, this dissertation makes a contribution by developing a structural dynamic model of GM technology adoption, which allows us to conduct a joint empirical analysis of dynamics, risk preferences, individual learning, and social learning (information externalities). It evaluates the joint impact on behavior of risk preferences and learning using the structural approach instead of the reduced-form approach. The reduced-form approach has been widely used by the previous adoption literature due to its relative ease but could not explain the roles of risk preferences and learning explicitly in a dynamic environment (e.g., a logistic model). Moreover, our structural adoption model involves a continuous choice DP problem, making the solution of relevant Bellman equation more complicated than most of previous literature counting on a discrete choice DP problem (Berry, 1994; Erdem and Keane, 1996; Manski, 1993). Thereby, our analysis contributes in expanding the literature on dynamic GM technology adoption and in specifying the joint roles of risk, learning, and information externalities in the context of dynamics.

Third, our research makes contributions to providing an empirical analysis incorporating model estimation into the DP model. While combining a dynamic optimization problem with model estimation is not new, empirical applications remain few due to the corresponding computational burden. This dissertation explores ways to make this analysis empirically tractable. It estimates model parameters by nesting a dynamic optimization problem within a minimum distance estimator. Specifically, we devise an algorithm to solve corresponding Bellman equation for GM technology adoption so as to minimize the distance between the model and observed data, estimating parameters associated with risk preferences, individual learning, and social learning simultaneously. The analysis is also used to conduct hypothesis testing, sensitivity analysis, and welfare analysis on key structural parameters of risk aversion and the social learning parameter. As such, this research proposes new ways to integrate econometric estimation and dynamic optimization.

Finally, our empirical analysis provides new and useful information on the role of risk, risk aversion, and social learning in GM technology adoption. Our results confirm the followings: First, farmers are risk averse in adopting new technologies (GM seeds). Second, both individual and social learning play a key role in adopting GM technology in positive directions with high statistical significance. Third, the impacts of individual learning are shown to be larger than the impacts of social learning. Further, our empirical results across farm types demonstrate that farmers adopt GM technology later as they are more risk-averse and rely more on social interactions (as information externalities are stronger).

7.3.Limitation & Future Research

While our research contributes to both methodological developments and empirical findings, it is limited for the followings: First, our hypothesis testing is conducted based on small samples. This was done trying to reduce the computational burden for our empirical analysis and to secure positive degree of freedoms for conducting F-tests. Thereby, econometric evidences may not be powerful due to small samples. In the context of parameterized DP models nested within econometric estimation, it would be useful to explore ways of conducting hypothesis testing based on larger sample. Second, we solve a single Bellman equation for each model assuming that all individual farmers are homogeneous within each group. We analyze three types of farmers and find evidence of parameter heterogeneity across groups. But additional heterogeneity may also exist across farmers within each group. Third, we analyze the roles of individual vs. social learning by parameterizing social interaction in the model. A more explicit analysis of strategic interactions would be helpful but remains with the issue of curse of dimensionality in the context of dynamics.

Future research is needed to extend our analysis in several directions. First, further refinements in numerical methods and the development of faster computer algorithms can help bridge the gap between dynamic optimization models and the empirical analysis of behavioral rules. By reducing the high computational burden we faced in this research, this would create new opportunities for advancements in our field of inquiries. Second, our analysis focuses on adoption choices involving just two technologies: conventional seed and GM seed. It would be useful to expand the choice set and to distinguish between several GM technologies (such as HT, IR-CB, and Stacked seed). Third, our analysis conveniently relied on the normality assumption. Noting that the Kalman filter can be applied to any distribution, it would be valuable to explore adoption and learning under broader distributional assumptions. These appear to be good topics for future research.

Appendix: Learning Process by the Kalman Filter Algorithm

The Kalman filter algorithm provides a useful tool to find the linear least-squares estimate of the unobservable state vector (e. g., the profitability π_t^k) given the previous estimate $\mu_{t|t-1}^k$ or $\Sigma_{t|t-1}$ and the new measurement z_t without history of measurements such as $z_0, z_1, ..., z_{t-1}$ (Berteskas, 1976).

It applies in general, providing a convenient representation of the evolving mean and variance associated with any distribution. For simplicity, we assume normality for the distribution of the unobservable states. By that assumption, the representation of learning process using the Kalman filter is consistent with the Bayesian updating rule utilizing conjugacy property of normal distribution (DeGroot, 1970).

Based on basic definitions of variables and parameters described in Chapter 3, we provide a generalized form of the Kalman filter algorithm. Assuming all the parameters are time invariant, the system equation and the measurement equation are considered as the following linear system of equations.

$$\boldsymbol{\pi}_{t+1} = \boldsymbol{\alpha}\boldsymbol{\pi}_t + \boldsymbol{\beta}\mathbf{x}_t + \boldsymbol{\chi}\mathbf{y}_t + \mathbf{v}_t \qquad \text{(the system equation) (A.1)}$$

$$\Leftrightarrow \begin{bmatrix} \pi_{t+1}^{CONV} \\ \pi_{t+1}^{GM} \end{bmatrix} = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix} \begin{bmatrix} \pi_t^{CONV} \\ \pi_t^{GM} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \begin{bmatrix} x_t^{CONV} \\ x_t^{GM} \end{bmatrix} + \begin{bmatrix} \chi_{11} & \chi_{12} \\ \chi_{21} & \chi_{22} \end{bmatrix} \begin{bmatrix} y_t^{CONV} \\ y_t^{GM} \end{bmatrix} + \begin{bmatrix} v_t^{CONV} \\ v_t^{GM} \end{bmatrix},$$

$$z_t = \boldsymbol{\gamma}\boldsymbol{\pi}_t + \mathbf{w}_t \qquad \text{(the measurement equation) (A.2)}$$

$$\Leftrightarrow \begin{bmatrix} q_{t-1}^{CONV} \\ y_{t-1}^{CONV} \\ q_{t-1}^{GM} \\ y_{t-1}^{GM} \end{bmatrix} = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \\ \gamma_{31} & \gamma_{32} \\ \gamma_{41} & \gamma_{42} \end{bmatrix} \begin{bmatrix} \pi_t^{CONV} \\ \pi_t^{GM} \end{bmatrix} + \begin{bmatrix} w_t^{q^{CONV}} \\ w_t^{y^{CONV}} \\ w_t^{q^{GM}} \\ w_t^{y^{GM}} \end{bmatrix},$$

where $\mathbf{y}_t = \begin{bmatrix} y_t^{CONV} & y_t^{GM} \end{bmatrix}^{\mathsf{T}}$ indicates a farmer's neighbors' adoption rates for each technology, and $\boldsymbol{\chi}$ is a 2-by-2 vector of corresponding parameters.[35] The vector of random disturbance $\mathbf{v}_t$ and the vector of observation noises $\mathbf{w}_t$ are assumed to be mutually independent. Also, both $\mathbf{v}_t$ and $\mathbf{w}_t$ are distributed with zero mean. The variance-covariance matrix in terms of $\mathbf{v}_t$ and $\mathbf{w}_t$ is described as

$$E\begin{bmatrix} (\mathbf{v}_t - E[\mathbf{v}_t])(\mathbf{v}_t - E[\mathbf{v}_t])^{\mathsf{T}} & (\mathbf{v}_t - E[\mathbf{v}_t])(\mathbf{w}_t - E[\mathbf{w}_t])^{\mathsf{T}} \\ (\mathbf{w}_t - E[\mathbf{w}_t])(\mathbf{w}_t - E[\mathbf{w}_t]) & (\mathbf{w}_t - E[\mathbf{w}_t])(\mathbf{w}_t - E[\mathbf{w}_t])^{\mathsf{T}} \end{bmatrix} = E\begin{bmatrix} \mathbf{v}_t\mathbf{v}_t^{\mathsf{T}} & \mathbf{v}_t\mathbf{w}_t^{\mathsf{T}} \\ \mathbf{w}_t\mathbf{v}_t^{\mathsf{T}} & \mathbf{w}_t\mathbf{w}_t^{\mathsf{T}} \end{bmatrix} = \begin{bmatrix} M_t & 0 \\ 0 & N_t \end{bmatrix}.$$

The first equality results from zero means of all the random disturbances, and the second equality is due to the assumption of mutual independence. Then, assumptions for $\mathbf{v}_t$ and $\mathbf{w}_t$ are summarized as

$$E[\mathbf{v}_t] = 0, E[\mathbf{w}_t] = 0, M_t = E\left[\mathbf{v}_t\mathbf{v}_t^{\mathsf{T}}\right], N_t = E\left[\mathbf{w}_t\mathbf{w}_t^{\mathsf{T}}\right] \tag{A.3}$$

$$\Leftrightarrow \quad \begin{bmatrix} E\left[v_t^{CONV}\right] & E\left[v_t^{GM}\right] \end{bmatrix}^{\mathsf{T}} = \begin{bmatrix} 0 & 0 \end{bmatrix}^{\mathsf{T}},$$

$$\begin{bmatrix} E\left[w_t^{q^{CONV}}\right] & E\left[w_t^{y^{CONV}}\right] & E\left[w_t^{q^{GM}}\right] & E\left[w_t^{y^{GM}}\right] \end{bmatrix}^{\mathsf{T}} = \begin{bmatrix} 0 & 0 & 0 & 0 \end{bmatrix}^{\mathsf{T}},$$

$$M_t = \begin{bmatrix} \sigma^2_{v_t^{CONV}} & 0 \\ 0 & \sigma^2_{v_t^{GM}} \end{bmatrix}, \text{ and } N_t = \begin{bmatrix} \sigma^2_{q_t^{CONV}} & 0 & 0 & 0 \\ 0 & \sigma^2_{y_t^{CONV}} & 0 & 0 \\ 0 & 0 & \sigma^2_{q_t^{GM}} & 0 \\ 0 & 0 & 0 & \sigma^2_{y_t^{GM}} \end{bmatrix}.$$

For each technology k, $\boldsymbol{\mu}_{t|t} = \begin{bmatrix} \mu_{t|t}^{CONV} & \mu_{t|t}^{GM} \end{bmatrix}^{\mathsf{T}}$ denotes the vector of the conditional means of the net profitability π_t^k given z_t. Also, $\Sigma_{t|t}$ denotes the conditional variance-

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[35] For a more general derivation, the term capturing neighbors' adoption rates $\boldsymbol{\chi}\mathbf{y}_t$ is added, but it is omitted in Chapter 3 for simplicity.

covariance matrix of the net profitability π_t^k given z_t with the conditional variance $\sigma_{t|t,k}^2$. The conditional mean and variance are regarded as the linear least-squares estimate of the unobservable state variables $\boldsymbol{\pi}_t$ given observable measurements $z_0, z_1, ..., z_{t-1}, z_t$. Note that the subscript $t|t$ implies the conditional moments at time period t are estimated given information up to time period t. If the subscript is represented as $t+1|t$, it implies that the conditional moments at time period $t+1$ are estimated given information up to time period t. Similarly, $t|t-1$ indicates the conditional moments at t are estimated given information up to $t-1$.

Suppose the linear system of equations (A.1) and (A.2) starts up at t = 0. The state vector of the net profitability for each technology at t = 0, $\boldsymbol{\pi}_0$ is regarded as a random vector with the mean $E[\boldsymbol{\pi}_0] = \boldsymbol{\mu}_0$ and the variance-covariance matrix Σ_0. The pair ($\boldsymbol{\mu}_0$, Σ_0) plays a role of the mean and variance-covariance matrix for a Bayesian prior distribution on $\boldsymbol{\pi}_0$ (Ljungqvist and Sargent, 2004, p. 1023). For simplicity, we assume that ($\boldsymbol{\mu}_0$, Σ_0) is given from the empirical data.

At each time period t, researchers are assumed to receive observable measurements z_t addressing information of the unobservable state vector $\boldsymbol{\pi}_t$. We define the history of previous measurements up to time period $t-1$ as

$$Z_{t-1} = \{z_0, z_1, ..., z_{t-1}\}. \tag{A.4}$$

Using the above definition, the relation between the history of measurements and a new measurement at time period t is derived as follows

$$Z_t = \{z_0, z_1, ..., z_{t-1}, z_t\} = \{Z_{t-1}, z_t\}. \tag{A.5}$$

At time period t, the previous estimate $\boldsymbol{\mu}_{t|t-1}$ are supposed to be calculated with its corresponding matrix $\Sigma_{t|t-1}$ defined as

$$\Sigma_{t|t-1} = E\left[\left(\boldsymbol{\pi}_t - \boldsymbol{\mu}_{t|t-1}\right)\left(\boldsymbol{\pi}_t - \boldsymbol{\mu}_{t|t-1}\right)^{\mathsf{T}}\right]. \tag{A.6}$$

Also, researchers are assumed to observe a new measurement z_t in addition to the previous measurements Z_{t-1} up to time period $t-1$. Then, our object is to compute the linear least-squares estimate of $\boldsymbol{\pi}_t$ given $Z_{t-1} = \{z_0, z_1, ..., z_{t-1}\}$ and z_t; that is, $\boldsymbol{\mu}_{t|t}$ and its corresponding variance-covariance matrix $\Sigma_{t|t}$. For this object, we employ useful theorems from Berteskas (1976).[36]

Theorem A.1.[37] *Consider A and B be random vectors whose mean and variance-covariance matrices are denoted as*

$$E[A] \textit{ and } E[B] \qquad \textit{(mean)}$$

$$E\left[\left(A-E[A]\right)\left(A-E[A]\right)^{\mathsf{T}}\right] = \operatorname{var}(A) \textit{ and } E\left[\left(B-E[B]\right)\left(B-E[B]\right)^{\mathsf{T}}\right] = \operatorname{var}(B) \quad \textit{(variance)}$$

$$E\left[\left(A-E[A]\right)\left(B-E[B]\right)^{\mathsf{T}}\right] = \operatorname{cov}(A,B) \textit{ and}$$

$$E\left[\left(B-E[B]\right)\left(A-E[A]\right)^{\mathsf{T}}\right] = \operatorname{cov}(B,A) = \operatorname{cov}(A,B)^{\mathsf{T}}. \qquad \textit{(covariance)}$$

Let's denote $\hat{E}[X \mid Y]$ as the linear least-squares estimate of X given Y. Then, the linear least-squares estimate of A given B is represented as

$$\hat{E}[A \mid B] = E[A] + \operatorname{cov}(A,B)\{\operatorname{var}(B)\}^{-1}\left[B - E[B]\right]. \tag{A.7}$$

And, its corresponding error covariance matrix is

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[36] Further details are referred to Berteskas (1976, p. 158).

[37] See Berteskas (1976, p. 162) or Ljungqvist and Sargent (2004, p. 1039) for the proof of Theorem A.1.

$$\underset{A,B}{E}\left[\left(A-\hat{E}[A \mid B]\right)\left(A-\hat{E}[A \mid B]\right)^{\top}\right]=\operatorname{var}(A)-\operatorname{cov}(A,B)\{\operatorname{var}(B)\}^{-1}\operatorname{cov}(B,A). \quad (A.8)$$

Theorem A.2.[38] *In addition to random vectors A and B in Theorem A.1, let C be an additional random vector correlated with B. That is,*

$$E\left[\left(B-E[B]\right)\left(C-E[C]\right)^{\top}\right]=\operatorname{cov}(B,C)\neq 0.$$

Then, the linear least-squares estimate of A given B and C in terms of the conditional mean is

$$\hat{E}[A \mid B,C]=\hat{E}[A \mid B]+\hat{E}\left[A \mid C-\hat{E}[C \mid B]\right]-E[A]. \quad (A.9)$$

Further, its corresponding variance-covariance matrix is

$$\underset{A,B,C}{E}\left[\left(A-\hat{E}[A \mid B,C]\right)\left(A-\hat{E}[A \mid B,C]\right)^{\top}\right]=\underset{A,B}{E}\left[\begin{array}{l}\left(A-\hat{E}(A \mid B)\right)\left(A-\hat{E}(A \mid B)\right)^{\top} \\ -\underset{A,B,C}{E}\left[\left(A-E[A]\right)\left(C-\hat{E}[C \mid B]\right)^{\top}\right]\end{array}\right]. \quad (A.10)$$
$$\times\left[\underset{B,C}{E}\left[\left(C-\hat{E}[C \mid B]\right)\left(C-\hat{E}[C \mid B]\right)^{\top}\right]\right]^{-1}\underset{A,B,C}{E}\left[\left(C-\hat{E}[C \mid B]\right)\left(A-E[A]\right)^{\top}\right]$$

Note that $\boldsymbol{\mu}_{t|t}$ indicates the linear least-squares estimate of $\boldsymbol{\pi}_t$ given information at time period t. Information at t includes the given initial value $\boldsymbol{\pi}_0$, the history of past measurements ($z_0, z_1, ..., z_{t-1}$), and a newly added measurement z_t. Applying notations in Theorem A.1 and Theorem A.2, $\boldsymbol{\mu}_{t|t}$ can be represented as

$$\boldsymbol{\mu}_{t|t}\equiv\hat{E}\left[\boldsymbol{\pi}_t \mid \boldsymbol{\pi}_0, z_0, z_1, ..., z_{t-1}, z_t\right]=\hat{E}\left[\boldsymbol{\pi}_t \mid \boldsymbol{\pi}_0, Z_{t-1}, z_t\right] \quad (A.11)$$

Then, using (A.9) in Theorem A.2, $\boldsymbol{\mu}_{t|t}$ can be described as

[38] Ljungqvist and Sargent (2004) call this theorem as *Orthogonal regressors*. For the proof of Theorem A.2, readers can also refer to Berteskas (1976, p. 166) or Ljungqvist and Sargent (2004, p. 1040).

$$\boldsymbol{\mu}_{t|t} \equiv \hat{E}\left[\boldsymbol{\pi}_t \mid \boldsymbol{\pi}_0, Z_{t-1}, z_t\right] = \hat{E}\left[\boldsymbol{\pi}_t \mid \boldsymbol{\pi}_0, Z_{t-1}\right] + \hat{E}\left[\boldsymbol{\pi}_t \mid z_t - \hat{E}\left[z_t \mid \boldsymbol{\pi}_0, Z_{t-1}\right]\right] - E\left[\boldsymbol{\pi}_t\right]$$

$$= \hat{E}\left[\boldsymbol{\pi}_t \mid \boldsymbol{\pi}_0, Z_{t-1}\right] + \hat{E}\left[\boldsymbol{\pi}_t \mid \tilde{z}_t\right] - E\left[\boldsymbol{\pi}_t\right]$$

$$= \boldsymbol{\mu}_{t|t-1} + \hat{E}\left[\boldsymbol{\pi}_t \mid \tilde{z}_t\right] - E\left[\boldsymbol{\pi}_t\right]. \qquad \text{(A.12)}$$

In the third equality, we define $\boldsymbol{\mu}_{t|t-1} \equiv \hat{E}\left[\boldsymbol{\pi}_t \mid \boldsymbol{\pi}_0, Z_{t-1}\right]$. In order to construct equations more conveniently, we apply a Gram-Schmidt orthogonalization procedure to the first equality of (A.12) (Ljungqvist and Sargent, 2004, p. 1024). Then, $\tilde{z}_t$ in the second equality is defined as

$$\tilde{z}_t = z_t - \hat{E}\left[z_t \mid \boldsymbol{\pi}_0, Z_{t-1}\right]. \qquad \text{(A.13)}$$

Taking the linear least-squares estimator operator $\hat{E}\left[\cdot \mid \cdot\right]$ to the measurement equation in (A.2) directly, we get the following equation of

$$\hat{E}\left[z_t \mid \boldsymbol{\pi}_0, Z_{t-1}\right] = \boldsymbol{\gamma}\hat{E}\left[\boldsymbol{\pi}_t \mid \boldsymbol{\pi}_0, Z_{t-1}\right] + E\left[\mathbf{w}_t \mid \boldsymbol{\pi}_0, Z_{t-1}\right]$$

$$= \boldsymbol{\gamma}\hat{E}\left[\boldsymbol{\pi}_t \mid \boldsymbol{\pi}_0, Z_{t-1}\right] + 0$$

$$= \boldsymbol{\gamma}\boldsymbol{\mu}_{t|t-1}. \qquad \text{(A.14)}$$

The second equality is valid due to the zero mean assumption of $\mathbf{w}_t$ in (A.3). Introducing (A.14) into (A.13), $\tilde{z}_t$ is represented as

$$\tilde{z}_t = z_t - \boldsymbol{\gamma}\boldsymbol{\mu}_{t|t-1}. \qquad \text{(A.15)}$$

Using (A.7) in Theorem A.1 with (A.15), the second term of the last equality in (A.12) can be described as

$$\hat{E}\left[\boldsymbol{\pi}_t \mid \tilde{z}_t\right] = E\left[\boldsymbol{\pi}_t\right] + \mathrm{cov}\left(\boldsymbol{\pi}_t, \tilde{z}_t\right)\left\{\mathrm{var}\left(\tilde{z}_t\right)\right\}^{-1}\left[\tilde{z}_t - E\left[\tilde{z}_t\right]\right]$$

$$= E\left[\boldsymbol{\pi}_t\right] + \mathrm{cov}\left(\boldsymbol{\pi}_t, \tilde{z}_t\right)\left\{\mathrm{var}\left(\tilde{z}_t\right)\right\}^{-1}\tilde{z}_t. \qquad \text{(A.16)}$$

The last component of the first equality in (A.16), $E\left[\tilde{z}_t\right]=E\left[z_t-\hat{E}\left[z_t \mid \boldsymbol{\pi}_0, Z_{t-1}\right]\right]$ becomes zero by the unbiased property of linear least-squares estimates when one of the regressors is a constant (Ljungqvist and Sargent, 2004, p. 1026). That is,

$$E\left[\tilde{z}_t\right]=E\left[z_t-\hat{E}\left[z_t \mid \boldsymbol{\pi}_0, Z_{t-1}\right]\right]=0. \tag{A.17}$$

Using (A.15), the variance term in (A.16), $\operatorname{var}\left(\tilde{z}_t\right)$ can be rewritten as follows:

$$\begin{aligned}
\operatorname{var}\left(\tilde{z}_t\right) &= E\left[\left(\tilde{z}_t-E\left[\tilde{z}_t\right]\right)\left(\tilde{z}_t-E\left[\tilde{z}_t\right]\right)^{\mathsf{T}}\right] \\
&= E\left[\left(\tilde{z}_t-0\right)\left(\tilde{z}_t-0\right)^{\mathsf{T}}\right] \\
&= E\left[\tilde{z}_t \tilde{z}_t^{\mathsf{T}}\right] \\
&= E\left[\left(z_t-\hat{E}\left[z_t \mid \boldsymbol{\pi}_0, Z_{t-1}\right]\right)\left(z_t-\hat{E}\left[z_t \mid \boldsymbol{\pi}_0, Z_{t-1}\right]\right)^{\mathsf{T}}\right].
\end{aligned} \tag{A.18}$$

The second equality results from (A.17), and the last equality comes from (A.13). Using the measurement equation (A.2) and results from (A.14), the variance term in (A.18) can be represented as

$$\begin{aligned}
\operatorname{var}\left(\tilde{z}_t\right) &= E\left[\left(\boldsymbol{\gamma}\boldsymbol{\pi}_t+\mathbf{w}_t-\boldsymbol{\gamma}\boldsymbol{\mu}_{t|t-1}\right)\left(\boldsymbol{\gamma}\boldsymbol{\pi}_t+\mathbf{w}_t-\boldsymbol{\gamma}\boldsymbol{\mu}_{t|t-1}\right)^{\mathsf{T}}\right] \\
&= E\left[\left(\boldsymbol{\gamma}\left(\boldsymbol{\pi}_t-\boldsymbol{\mu}_{t|t-1}\right)+\mathbf{w}_t\right)\left(\boldsymbol{\gamma}\left(\boldsymbol{\pi}_t-\boldsymbol{\mu}_{t|t-1}\right)+\mathbf{w}_t\right)^{\mathsf{T}}\right].
\end{aligned} \tag{A.19}$$

Again, we apply a Gram-Schmidt orthogonalization procedure for $\boldsymbol{\pi}_t$. Then the difference between $\boldsymbol{\pi}_t$ and its least-squares estimate given information at $t-1$, $\boldsymbol{\mu}_{t|t-1}$ is defined as

$$\tilde{\boldsymbol{\pi}}_t \equiv \boldsymbol{\pi}_t-\boldsymbol{\mu}_{t|t-1}=\boldsymbol{\pi}_t-\hat{E}\left[\boldsymbol{\pi}_t \mid \boldsymbol{\pi}_0, Z_{t-1}\right]. \tag{A.20}$$

In addition, the unbiased property of linear least-squares estimates leads to

$$E\left[\tilde{\boldsymbol{\pi}}_t\right]=E\left[\boldsymbol{\pi}_t-\boldsymbol{\mu}_{t|t-1}\right]=E\left[\boldsymbol{\pi}_t-\hat{E}\left[\boldsymbol{\pi}_t \mid \boldsymbol{\pi}_0, Z_{t-1}\right]\right]=0. \tag{A.21}$$

Applying (A.20) with $E[\mathbf{w}_t] = 0$ and $E\left[\mathbf{w}_t\mathbf{w}_t^{\mathsf{T}}\right] \equiv N_t$ in (A.3) to Equation (A.19), the variance term is rewritten as

$$\begin{aligned}\operatorname{var}(\tilde{z}_t) &= E\left[(\boldsymbol{\gamma}\tilde{\boldsymbol{\pi}}_t + \mathbf{w}_t)(\boldsymbol{\gamma}\tilde{\boldsymbol{\pi}}_t + \mathbf{w}_t)^{\mathsf{T}}\right] \\ &= E\left[\boldsymbol{\gamma}\tilde{\boldsymbol{\pi}}_t\tilde{\boldsymbol{\pi}}_t^{\mathsf{T}}\boldsymbol{\gamma}^{\mathsf{T}}\right] + E\left[\mathbf{w}_t\mathbf{w}_t^{\mathsf{T}}\right] \\ &= \boldsymbol{\gamma}E\left[\tilde{\boldsymbol{\pi}}_t\tilde{\boldsymbol{\pi}}_t^{\mathsf{T}}\right]\boldsymbol{\gamma}^{\mathsf{T}} + N_t. \end{aligned} \tag{A.22}$$

The first component of the last equality in (A.22) indicates the linear least-squares estimate $\boldsymbol{\mu}_{t|t-1}$'s corresponding error covariance matrix defined as

$$\Sigma_{t|t-1} \equiv E\left[\left(\boldsymbol{\pi}_t - \hat{E}[\boldsymbol{\pi}_t \mid \boldsymbol{\pi}_0, Z_{t-1}]\right)\left(\boldsymbol{\pi}_t - \hat{E}[\boldsymbol{\pi}_t \mid \boldsymbol{\pi}_0, Z_{t-1}]\right)^{\mathsf{T}}\right] = E\left[\tilde{\boldsymbol{\pi}}_t\tilde{\boldsymbol{\pi}}_t^{\mathsf{T}}\right]. \tag{A.23}$$

From (A.22) and (A.23), the variance matrix of $\tilde{z}_t$ is summarized as

$$\operatorname{var}(\tilde{z}_t) = \boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}} + N_t. \tag{A.24}$$

Next, the covariance term in (A.16), $\operatorname{cov}(\boldsymbol{\pi}_t, \tilde{z}_t)$ can be considered as

$$\begin{aligned}\operatorname{cov}(\boldsymbol{\pi}_t, \tilde{z}_t) &= E\left[\left(\boldsymbol{\pi}_t - E[\boldsymbol{\pi}_t]\right)\left(\tilde{z}_t - E[\tilde{z}_t]\right)^{\mathsf{T}}\right] \\ &= E\left[\left(\boldsymbol{\pi}_t - E[\boldsymbol{\pi}_t]\right)(\tilde{z}_t - 0)^{\mathsf{T}}\right] \\ &= E\left[\left(\boldsymbol{\pi}_t - E[\boldsymbol{\pi}_t]\right)\cdot \tilde{z}_t^{\mathsf{T}}\right] \\ &= E\left[\left(\boldsymbol{\pi}_t - E[\boldsymbol{\pi}_t]\right)\left(z_t - \hat{E}[z_t \mid \boldsymbol{\pi}_0, Z_{t-1}]\right)^{\mathsf{T}}\right]. \end{aligned} \tag{A.25}$$

Using the measurement equation (A.2) and the definition of $\tilde{z}_t$ in (A.15), the covariance term (A.25) is represented as

$$\operatorname{cov}(\boldsymbol{\pi}_t, \tilde{z}_t) = E\left[\left(\boldsymbol{\pi}_t - E[\boldsymbol{\pi}_t]\right)\cdot\left(\boldsymbol{\gamma}\boldsymbol{\pi}_t + \mathbf{w}_t - \boldsymbol{\gamma}\boldsymbol{\mu}_{t|t-1}\right)^{\mathsf{T}}\right]$$

$$= E\left[\boldsymbol{\pi}_t \cdot \left[\boldsymbol{\gamma} \cdot \left(\boldsymbol{\pi}_t - \boldsymbol{\mu}_{t|t-1}\right)\right]^\top - E\left[\boldsymbol{\pi}_t\right] \cdot \left[\boldsymbol{\gamma} \cdot \left(\boldsymbol{\pi}_t - \boldsymbol{\mu}_{t|t-1}\right)\right]^\top + \boldsymbol{\pi}_t \mathbf{w}_t^\top - E\left[\boldsymbol{\pi}_t\right] \cdot \mathbf{w}_t^\top\right]$$

$$= E\left[\boldsymbol{\pi}_t \cdot \left[\boldsymbol{\gamma} \cdot \tilde{\boldsymbol{\pi}}_t\right]^\top - E\left[\boldsymbol{\pi}_t\right] \cdot \left[\boldsymbol{\gamma} \cdot \tilde{\boldsymbol{\pi}}_t\right]^\top + \boldsymbol{\pi}_t \mathbf{w}_t^\top - E\left[\boldsymbol{\pi}_t\right] \cdot \mathbf{w}_t^\top\right]$$

$$= E\left[\boldsymbol{\pi}_t \cdot \left[\boldsymbol{\gamma} \cdot \tilde{\boldsymbol{\pi}}_t\right]^\top\right] - E\left[\boldsymbol{\pi}_t\right] \cdot \boldsymbol{\gamma} \cdot E\left[\tilde{\boldsymbol{\pi}}_t^\top\right] + E\left[\boldsymbol{\pi}_t \mathbf{w}_t^\top\right] - E\left[\boldsymbol{\pi}_t\right] \cdot E\left[\mathbf{w}_t^\top\right]$$

$$= E\left[\boldsymbol{\pi}_t \cdot \left[\boldsymbol{\gamma} \cdot \tilde{\boldsymbol{\pi}}_t\right]^\top\right] - 0 + 0 - 0$$

$$= E\left[\boldsymbol{\pi}_t \cdot \left[\boldsymbol{\gamma} \cdot \left(\boldsymbol{\pi}_t - \boldsymbol{\mu}_{t|t-1}\right)\right]^\top\right]$$

$$= E\left[\boldsymbol{\pi}_t \cdot \left(\boldsymbol{\pi}_t - \boldsymbol{\mu}_{t|t-1}\right)^\top\right] \cdot \boldsymbol{\gamma}^\top$$

$$= E\left[\left(\boldsymbol{\pi}_t - \boldsymbol{\mu}_{t|t-1} + \boldsymbol{\mu}_{t|t-1}\right) \cdot \left(\boldsymbol{\pi}_t - \boldsymbol{\mu}_{t|t-1}\right)^\top\right] \cdot \boldsymbol{\gamma}^\top$$

$$= E\left[\left(\boldsymbol{\pi}_t - \boldsymbol{\mu}_{t|t-1}\right) \cdot \left(\boldsymbol{\pi}_t - \boldsymbol{\mu}_{t|t-1}\right)^\top\right] \cdot \boldsymbol{\gamma}^\top + E\left[\boldsymbol{\mu}_{t|t-1} \cdot \left(\boldsymbol{\pi}_t - \boldsymbol{\mu}_{t|t-1}\right)^\top\right] \cdot \boldsymbol{\gamma}^\top$$

$$= E\left[\left(\boldsymbol{\pi}_t - \boldsymbol{\mu}_{t|t-1}\right) \cdot \left(\boldsymbol{\pi}_t - \boldsymbol{\mu}_{t|t-1}\right)^\top\right] \cdot \boldsymbol{\gamma}^\top + 0$$

$$= E\left[\tilde{\boldsymbol{\pi}}_t \tilde{\boldsymbol{\pi}}_t^\top\right] \cdot \boldsymbol{\gamma}^\top . \tag{A.26}$$

The fifth equality results from $E\left[\tilde{\boldsymbol{\pi}}_t\right] = 0$ in (A.21) and assumptions concerning $\mathbf{w}_t$ in (A.3) ($E\left[\mathbf{w}_t\right] = 0$ and $E\left[\mathbf{w}_t \mathbf{w}_t^\top\right] \equiv N_t$). A trick of adding and subtracting $\boldsymbol{\mu}_{t|t-1}$ is used in the eighth equality so as to derive the ninth equality. Using the definition of $\tilde{\boldsymbol{\pi}}_t$ in (A.20) and $E\left[\tilde{\boldsymbol{\pi}}_t\right] = 0$ in (A.21), the tenth equality and the eleventh equality are derived. Using the definition of $\Sigma_{t|t-1}$ in (A.23), the covariance term in (A.26) can be represented as

$$\operatorname{cov}\left(\boldsymbol{\pi}_t, \tilde{z}_t\right) = \Sigma_{t|t-1} \cdot \boldsymbol{\gamma}^\top . \tag{A.27}$$

Now, we replace $\operatorname{cov}(\boldsymbol{\pi}_t, \tilde{z}_t)$ in (A.16) by the result of (A.24) and $\operatorname{var}(\tilde{z}_t)$ in (A.16) by the result of (A.27). Then, Equation (A.16) is rewritten as

$$\hat{E}\left[\boldsymbol{\pi}_t \mid \tilde{z}_t\right] = E\left[\boldsymbol{\pi}_t\right] + \Sigma_{t|t-1} \cdot \boldsymbol{\gamma}^{\mathsf{T}} \cdot \left\{\boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}} + N_t\right\}^{-1} \tilde{z}_t\,. \tag{A.28}$$

The first component of the last equality in (A.12), $\boldsymbol{\mu}_{t|t-1} \equiv \hat{E}\left[\boldsymbol{\pi}_t \mid \boldsymbol{\pi}_0, Z_{t-1}\right]$ can be expressed in terms of components in the system equation as follows: first, we consider the one-step lagged system equation from (A.1)

$$\boldsymbol{\pi}_t = \boldsymbol{\alpha}\boldsymbol{\pi}_{t-1} + \boldsymbol{\beta}\mathbf{x}_{t-1} + \boldsymbol{\chi}\mathbf{y}_{t-1} + \mathbf{v}_{t-1}\,. \tag{A.29}$$

Second, we take the linear least-squares estimator operator $\hat{E}\left[\cdot \mid \cdot\right]$ to (A.29) directly. That is,

$$\begin{aligned}
\hat{E}\left[\boldsymbol{\pi}_t \mid \boldsymbol{\pi}_0, Z_{t-1}\right] &= \boldsymbol{\alpha}\hat{E}\left[\boldsymbol{\pi}_{t-1} \mid \boldsymbol{\pi}_0, Z_{t-1}\right] + \hat{E}\left[\boldsymbol{\beta}\mathbf{x}_{t-1} + \boldsymbol{\chi}\mathbf{y}_{t-1} \mid \boldsymbol{\pi}_0, Z_{t-1}\right] + \hat{E}\left[\mathbf{v}_{t-1} \mid \boldsymbol{\pi}_0, Z_{t-1}\right] \\
&= \boldsymbol{\alpha}\hat{E}\left[\boldsymbol{\pi}_{t-1} \mid \boldsymbol{\pi}_0, Z_{t-1}\right] + \boldsymbol{\beta}\mathbf{x}_{t-1} + \boldsymbol{\chi}\mathbf{y}_{t-1} + 0 \\
&= \boldsymbol{\alpha}\hat{E}\left[\boldsymbol{\pi}_{t-1} \mid \boldsymbol{\pi}_0, Z_{t-1}\right] + \boldsymbol{\beta}\mathbf{x}_{t-1} + \boldsymbol{\chi}\mathbf{y}_{t-1}.
\end{aligned} \tag{A.30}$$

The second equality holds as $\boldsymbol{\beta}\mathbf{x}_{t-1}$ and $\boldsymbol{\chi}\mathbf{y}_{t-1}$ are not random vectors, and $E\left[\mathbf{v}_t\right] = 0$ in (A.3). Using simpler notations, (A.30) can be expressed as

$$\boldsymbol{\mu}_{t|t-1} = \boldsymbol{\alpha}\boldsymbol{\mu}_{t-1|t-1} + \boldsymbol{\beta}\mathbf{x}_{t-1} + \boldsymbol{\chi}\mathbf{y}_{t-1}\,. \tag{A.31}$$

Then, we incorporate results from (A.28) and (A.31) into Equation (A.12) as follows:

$$\begin{aligned}
\boldsymbol{\mu}_{t|t} &= \boldsymbol{\alpha}\boldsymbol{\mu}_{t-1|t-1} + \boldsymbol{\beta}\mathbf{x}_{t-1} + \boldsymbol{\chi}\mathbf{y}_{t-1} + E\left[\boldsymbol{\pi}_t\right] + \Sigma_{t|t-1} \cdot \boldsymbol{\gamma}^{\mathsf{T}} \cdot \left\{\boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}} + N_t\right\}^{-1} \tilde{z}_t - E\left[\boldsymbol{\pi}_t\right] \\
&= \boldsymbol{\alpha}\boldsymbol{\mu}_{t-1|t-1} + \boldsymbol{\beta}\mathbf{x}_{t-1} + \boldsymbol{\chi}\mathbf{y}_{t-1} + \Sigma_{t|t-1} \cdot \boldsymbol{\gamma}^{\mathsf{T}} \cdot \left\{\boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}} + N_t\right\}^{-1} \tilde{z}_t \\
&= \boldsymbol{\alpha}\boldsymbol{\mu}_{t-1|t-1} + \boldsymbol{\beta}\mathbf{x}_{t-1} + \boldsymbol{\chi}\mathbf{y}_{t-1} + \Sigma_{t|t-1} \cdot \boldsymbol{\gamma}^{\mathsf{T}} \cdot \left\{\boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}} + N_t\right\}^{-1} \cdot \left(z_t - \boldsymbol{\gamma}\boldsymbol{\mu}_{t|t-1}\right) \\
&= \boldsymbol{\alpha}\boldsymbol{\mu}_{t-1|t-1} + \boldsymbol{\beta}\mathbf{x}_{t-1} + \boldsymbol{\chi}\mathbf{y}_{t-1} + K_t \cdot \left(z_t - \boldsymbol{\gamma}\boldsymbol{\mu}_{t|t-1}\right),
\end{aligned} \tag{A.32}$$

where $K_t = \Sigma_{t|t-1} \cdot \boldsymbol{\gamma}^{\mathsf{T}} \cdot \left\{ \boldsymbol{\gamma} \Sigma_{t|t-1} \boldsymbol{\gamma}^{\mathsf{T}} + N_t \right\}^{-1}$, being called as the "Kalman-gain coefficient" (Ljungqvist and Sargent, 2004, p. 1028). In order to handle $\boldsymbol{\mu}_{t|t-1}$, we substitute the result of (A.31) for $\boldsymbol{\mu}_{t|t-1}$ in (A.32). That is,

$$\begin{aligned}
\boldsymbol{\mu}_{t|t} &= \boldsymbol{\alpha\mu}_{t-1|t-1} + \boldsymbol{\beta x}_{t-1} + \boldsymbol{\chi y}_{t-1} + K_t \left(z_t - \boldsymbol{\gamma} \cdot \left(\boldsymbol{\alpha\mu}_{t-1|t-1} + \boldsymbol{\beta x}_{t-1} + \boldsymbol{\chi y}_{t-1} \right) \right) \\
&= \boldsymbol{\alpha\mu}_{t-1|t-1} + \boldsymbol{\beta x}_{t-1} + \boldsymbol{\chi y}_{t-1} + K_t z_t - K_t \boldsymbol{\gamma} \left(\boldsymbol{\alpha\mu}_{t-1|t-1} + \boldsymbol{\beta x}_{t-1} + \boldsymbol{\chi y}_{t-1} \right) \\
&= \boldsymbol{\alpha\mu}_{t-1|t-1} + \boldsymbol{\beta x}_{t-1} + \boldsymbol{\chi y}_{t-1} + K_t z_t - K_t \boldsymbol{\gamma\alpha\mu}_{t-1|t-1} - K_t \boldsymbol{\gamma\beta x}_{t-1} - K_t \boldsymbol{\gamma\chi y}_{t-1} \\
&= \left(I - K_t \boldsymbol{\gamma} \right) \boldsymbol{\alpha\mu}_{t-1|t-1} + \left(I - K_t \boldsymbol{\gamma} \right) \boldsymbol{\beta x}_{t-1} + \left(I - K_t \boldsymbol{\gamma} \right) \boldsymbol{\chi y}_{t-1} + K_t z_t \,, \qquad \text{(A.33)}
\end{aligned}$$

$$\text{where } K_t = \Sigma_{t|t-1} \cdot \boldsymbol{\gamma}^{\mathsf{T}} \cdot \left\{ \boldsymbol{\gamma} \Sigma_{t|t-1} \boldsymbol{\gamma}^{\mathsf{T}} + N_t \right\}^{-1}. \qquad \text{(A.34)}$$

I indicates an identity matrix. Then, the one-step forward equation of (A.33) is represented as

$$\boldsymbol{\mu}_{t+1|t+1} = \left(I - K_{t+1} \boldsymbol{\gamma} \right) \boldsymbol{\alpha\mu}_{t|t} + \left(I - K_{t+1} \boldsymbol{\gamma} \right) \boldsymbol{\beta x}_t + \left(I - K_{t+1} \boldsymbol{\gamma} \right) \boldsymbol{\chi y}_t + K_{t+1} z_{t+1}, \qquad \text{(A.35)}$$

$$\text{where } K_{t+1} = \Sigma_{t+1|t} \cdot \boldsymbol{\gamma}^{\mathsf{T}} \cdot \left\{ \boldsymbol{\gamma} \Sigma_{t+1|t} \boldsymbol{\gamma}^{\mathsf{T}} + N_{t+1} \right\}^{-1}. \qquad \text{(A.36)}$$

Thereby, Equation (A.35) and Equation (A.36) generate the linear least-squares estimates $\boldsymbol{\mu}_{t|t}$ recursively together with the associated error covariance matrix $\Sigma_{t+1|t}$.

For our empirical research, it is preferred to consider $\Sigma_{t|t}$ ($\Sigma_{t+1|t+1}$) rather than $\Sigma_{t|t-1}$ ($\Sigma_{t+1|t}$). Thus, our next step is to obtain $\Sigma_{t|t}$ from Equation (A.36) expressed in terms of $\Sigma_{t+1|t}$. First, we obtain the one-step forward equation of (A.31) as

$$\boldsymbol{\mu}_{t+1|t} = \boldsymbol{\alpha\mu}_{t|t} + \boldsymbol{\beta x}_t + \boldsymbol{\chi y}_t \,. \qquad \text{(A.37)}$$

Then, the corresponding error covariance matrix $\Sigma_{t+1|t}$ is represented as

$$\Sigma_{t+1|t} = E\left[\left(\boldsymbol{\pi}_{t+1} - \boldsymbol{\mu}_{t+1|t}\right)\left(\boldsymbol{\pi}_{t+1} - \boldsymbol{\mu}_{t+1|t}\right)^{\mathsf{T}}\right]$$

$$= E\begin{bmatrix}\left(\boldsymbol{\alpha\pi}_t + \boldsymbol{\beta}\mathbf{x}_t + \boldsymbol{\chi}\mathbf{y}_t + \mathbf{v}_t - \left(\boldsymbol{\alpha\mu}_{t|t} + \boldsymbol{\beta}\mathbf{x}_t + \boldsymbol{\chi}\mathbf{y}_t\right)\right) \\ \times\left(\boldsymbol{\alpha\pi}_t + \boldsymbol{\beta}\mathbf{x}_t + \boldsymbol{\chi}\mathbf{y}_t + \mathbf{v}_t - \left(\boldsymbol{\alpha\mu}_{t|t} + \boldsymbol{\beta}\mathbf{x}_t + \boldsymbol{\chi}\mathbf{y}_t\right)\right)^{\mathsf{T}}\end{bmatrix}$$

$$= E\left[\left(\boldsymbol{\alpha\pi}_t - \boldsymbol{\alpha\mu}_{t|t} + \mathbf{v}_t\right)\left(\boldsymbol{\alpha\pi}_t - \boldsymbol{\alpha\mu}_{t|t} + \mathbf{v}_t\right)^{\mathsf{T}}\right]$$

$$= E\begin{bmatrix}\boldsymbol{\alpha\pi}_t\boldsymbol{\pi}_t^{\mathsf{T}}\boldsymbol{\alpha}^{\mathsf{T}} + \mathbf{v}_t\boldsymbol{\pi}_t^{\mathsf{T}}\boldsymbol{\alpha}^{\mathsf{T}} - \boldsymbol{\alpha\mu}_{t|t}\boldsymbol{\pi}_t^{\mathsf{T}}\boldsymbol{\alpha}^{\mathsf{T}} + \boldsymbol{\alpha\pi}_t\mathbf{v}_t^{\mathsf{T}} + \mathbf{v}_t\mathbf{v}_t^{\mathsf{T}} \\ -\boldsymbol{\alpha\mu}_{t|t}\mathbf{v}_t^{\mathsf{T}} - \boldsymbol{\alpha\pi}_t\boldsymbol{\mu}_{t|t}^{\mathsf{T}}\boldsymbol{\alpha}^{\mathsf{T}} - \mathbf{v}_t\boldsymbol{\mu}_{t|t}^{\mathsf{T}}\boldsymbol{\alpha}^{\mathsf{T}} + \boldsymbol{\alpha\mu}_{t|t}\boldsymbol{\mu}_{t|t}^{\mathsf{T}}\boldsymbol{\alpha}^{\mathsf{T}}\end{bmatrix}$$

$$\begin{aligned}= {} & E\left[\boldsymbol{\alpha\pi}_t\boldsymbol{\pi}_t^{\mathsf{T}}\boldsymbol{\alpha}^{\mathsf{T}}\right] + E\left[\mathbf{v}_t\boldsymbol{\pi}_t^{\mathsf{T}}\boldsymbol{\alpha}^{\mathsf{T}}\right] - E\left[\boldsymbol{\alpha\mu}_{t|t}\boldsymbol{\pi}_t^{\mathsf{T}}\boldsymbol{\alpha}^{\mathsf{T}}\right] + E\left[\boldsymbol{\alpha\pi}_t\mathbf{v}_t^{\mathsf{T}}\right] + E\left[\mathbf{v}_t\mathbf{v}_t^{\mathsf{T}}\right] \\ & -E\left[\boldsymbol{\alpha\mu}_{t|t}\mathbf{v}_t^{\mathsf{T}}\right] - E\left[\boldsymbol{\alpha\pi}_t\boldsymbol{\mu}_{t|t}^{\mathsf{T}}\boldsymbol{\alpha}^{\mathsf{T}}\right] - E\left[\mathbf{v}_t\boldsymbol{\mu}_{t|t}^{\mathsf{T}}\boldsymbol{\alpha}^{\mathsf{T}}\right] + E\left[\boldsymbol{\alpha\mu}_{t|t}\boldsymbol{\mu}_{t|t}^{\mathsf{T}}\boldsymbol{\alpha}^{\mathsf{T}}\right]\end{aligned}$$

$$\begin{aligned}= {} & E\left[\boldsymbol{\alpha\pi}_t\boldsymbol{\pi}_t^{\mathsf{T}}\boldsymbol{\alpha}^{\mathsf{T}}\right] + 0 - E\left[\boldsymbol{\alpha\mu}_{t|t}\boldsymbol{\pi}_t^{\mathsf{T}}\boldsymbol{\alpha}^{\mathsf{T}}\right] + 0 + M_t - 0 - E\left[\boldsymbol{\alpha\pi}_t\boldsymbol{\mu}_{t|t}^{\mathsf{T}}\boldsymbol{\alpha}^{\mathsf{T}}\right] \\ & -0 + E\left[\boldsymbol{\alpha\mu}_{t|t}\boldsymbol{\mu}_{t|t}^{\mathsf{T}}\boldsymbol{\alpha}^{\mathsf{T}}\right]\end{aligned}$$

$$= \boldsymbol{\alpha}E\left[\boldsymbol{\pi}_t\boldsymbol{\pi}_t^{\mathsf{T}} - \boldsymbol{\mu}_{t|t}\boldsymbol{\pi}_t^{\mathsf{T}} - \boldsymbol{\pi}_t\boldsymbol{\mu}_{t|t}^{\mathsf{T}} + \boldsymbol{\mu}_{t|t}\boldsymbol{\mu}_{t|t}^{\mathsf{T}}\right]\boldsymbol{\alpha}^{\mathsf{T}} + M_t$$

$$= \boldsymbol{\alpha}E\left[\left(\boldsymbol{\pi}_t - \boldsymbol{\mu}_{t|t}\right)\boldsymbol{\pi}_t^{\mathsf{T}} - \left(\boldsymbol{\pi}_t - \boldsymbol{\mu}_{t|t}\right)\boldsymbol{\mu}_{t|t}^{\mathsf{T}}\right]\boldsymbol{\alpha}^{\mathsf{T}} + M_t$$

$$= \boldsymbol{\alpha}E\left[\left(\boldsymbol{\pi}_t - \boldsymbol{\mu}_{t|t}\right)\left(\boldsymbol{\pi}_t^{\mathsf{T}} - \boldsymbol{\mu}_{t|t}^{\mathsf{T}}\right)\right]\boldsymbol{\alpha}^{\mathsf{T}} + M_t$$

$$= \boldsymbol{\alpha}E\left[\left(\boldsymbol{\pi}_t - \boldsymbol{\mu}_{t|t}\right)\left(\boldsymbol{\pi}_t - \boldsymbol{\mu}_{t|t}\right)^{\mathsf{T}}\right]\boldsymbol{\alpha}^{\mathsf{T}} + M_t$$

$$= \boldsymbol{\alpha}E\left[\tilde{\boldsymbol{\pi}}_t\tilde{\boldsymbol{\pi}}_t^{\mathsf{T}}\right]\boldsymbol{\alpha}^{\mathsf{T}} + M_t$$

$$= \boldsymbol{\alpha}\Sigma_{t|t}\boldsymbol{\alpha}^{\mathsf{T}} + M_t\,. \tag{A.38}$$

The first equality results from the definition of the error covariance matrix. The second equality is obtained by substituting (A.1) for $\boldsymbol{\pi}_{t+1}$ and (A.37) for $\boldsymbol{\mu}_{t+1|t}$ in the first equality. Zeros in the sixth equality are from the orthogonality between $\mathbf{v}_t$ and $\boldsymbol{\pi}_t$ (i. e., $E\left[\mathbf{v}_t\boldsymbol{\pi}_t\right] = E\left[\boldsymbol{\pi}_t\mathbf{v}_t\right] = 0$) and the zero mean assumption in (A.3), $E[\mathbf{v}_t]=0$. The eleventh equality results from the definition of $\tilde{\boldsymbol{\pi}}_t$ in (A.20).

Using (A.10) of Theorem A.2, the error covariance matrix $\Sigma_{t|t}$ is represented as

$$\Sigma_{t|t} \equiv E\left[\left(\boldsymbol{\pi}_t - \boldsymbol{\mu}_{t|t}\right)\left(\boldsymbol{\pi}_t - \boldsymbol{\mu}_{t|t}\right)^{\mathsf{T}}\right]$$

$$= E\left[\left(\boldsymbol{\pi}_t - \boldsymbol{\mu}_{t|t-1}\right)\left(\boldsymbol{\pi}_t - \boldsymbol{\mu}_{t|t-1}\right)^{\mathsf{T}}\right] - E\left[\left(\boldsymbol{\pi}_t - E[\boldsymbol{\pi}_t]\right)\left(z_t - \hat{E}[z_t \mid \boldsymbol{\pi}_0, Z_{t-1}]\right)^{\mathsf{T}}\right]$$

$$\times\left\{E\left[\left(\left(z_t - \hat{E}[z_t \mid \boldsymbol{\pi}_0, Z_{t-1}]\right)\left(z_t - \hat{E}[z_t \mid \boldsymbol{\pi}_0, Z_{t-1}]\right)^{\mathsf{T}}\right)\right]\right\}^{-1}$$

$$\times E\left[\left(z_t - \hat{E}[z_t \mid \boldsymbol{\pi}_0, Z_{t-1}]\right)\left(\boldsymbol{\pi}_t - E[\boldsymbol{\pi}_t]\right)^{\mathsf{T}}\right]. \tag{A.39}$$

The first component of (A.39) is described as follows by its definition:

$$\Sigma_{t|t-1} \equiv E\left[\left(\boldsymbol{\pi}_t - \boldsymbol{\mu}_{t|t-1}\right)\left(\boldsymbol{\pi}_t - \boldsymbol{\mu}_{t|t-1}\right)^{\mathsf{T}}\right]. \tag{A.40}$$

Using the result of (A.27), the second component of (A.39) can be rewritten as follows

$$E\left[\left(\boldsymbol{\pi}_t - E[\boldsymbol{\pi}_t]\right)\left(z_t - \hat{E}[z_t \mid \boldsymbol{\pi}_0, Z_{t-1}]\right)^{\mathsf{T}}\right] = E\left[\left(\boldsymbol{\pi}_t - E[\boldsymbol{\pi}_t]\right)\tilde{z}_t^{\mathsf{T}}\right]$$

$$= E\left[\left(\boldsymbol{\pi}_t - E[\boldsymbol{\pi}_t]\right)\left(\tilde{z}_t - 0\right)^{\mathsf{T}}\right]$$

$$= E\left[\left(\boldsymbol{\pi}_t - E[\boldsymbol{\pi}_t]\right)\left(\tilde{z}_t - E[\tilde{z}_t]\right)^{\mathsf{T}}\right]$$

$$= \operatorname{cov}\left(\boldsymbol{\pi}_t, \tilde{z}_t\right)$$

$$= \Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}}. \tag{A.41}$$

Also, using the result of (A.24), the third component of (A.39) is represented as

$$E\left[\left(\left(z_t - \hat{E}[z_t \mid \boldsymbol{\pi}_0, Z_{t-1}]\right)\left(z_t - \hat{E}[z_t \mid \boldsymbol{\pi}_0, Z_{t-1}]\right)^{\mathsf{T}}\right)\right] = E\left[\tilde{z}_t\tilde{z}_t^{\mathsf{T}}\right]$$

$$= E\left[\left(\tilde{z}_t - 0 \right) \left(\tilde{z}_t - 0 \right)^{\mathsf{T}} \right]$$

$$= E\left[\left(\tilde{z}_t - E\left[\tilde{z}_t \right] \right) \left(\tilde{z}_t - E\left[\tilde{z}_t \right] \right)^{\mathsf{T}} \right]$$

$$= \operatorname{var}\left(\tilde{z}_t \right)$$

$$= \boldsymbol{\gamma} \Sigma_{t|t-1} \boldsymbol{\gamma}^{\mathsf{T}} + N_t \,. \tag{A.42}$$

Using the result of (A.27), the last component of (A.39) is represented as

$$E\left[\left(z_t - \hat{E}\left[z_t \mid \boldsymbol{\pi}_0, Z_{t-1} \right] \right) \left(\boldsymbol{\pi}_t - E\left[\boldsymbol{\pi}_t \right] \right)^{\mathsf{T}} \right] = E\left[\left(\left(\boldsymbol{\pi}_t - E\left[\boldsymbol{\pi}_t \right] \right) \left(z_t - \hat{E}\left[z_t \mid \boldsymbol{\pi}_0, Z_{t-1} \right] \right)^{\mathsf{T}} \right)^{\mathsf{T}} \right]$$

$$= \left[E\left[\left(\boldsymbol{\pi}_t - E\left[\boldsymbol{\pi}_t \right] \right) \left(z_t - \hat{E}\left[z_t \mid \boldsymbol{\pi}_0, Z_{t-1} \right] \right)^{\mathsf{T}} \right] \right]^{\mathsf{T}}$$

$$= \left[\operatorname{cov}\left(\pi_t, \tilde{z}_t \right) \right]^{\mathsf{T}}$$

$$= \left[\Sigma_{t|t-1} \boldsymbol{\gamma}^{\mathsf{T}} \right]^{\mathsf{T}}$$

$$= \boldsymbol{\gamma} \Sigma_{t|t-1}^{\mathsf{T}}$$

$$= \boldsymbol{\gamma} \Sigma_{t|t-1} \,. \tag{A.43}$$

The last equation holds as $\Sigma_{t|t-1}^{\mathsf{T}} = \Sigma_{t|t-1}$ through Theorem A.1 ($\operatorname{cov}(A, B) = \operatorname{cov}(B, A)^{\mathsf{T}}$). Finally, results of (A.40), (A.41), (A.42), and (A.43) are incorporated into (A.39), giving the following equation

$$\Sigma_{t|t} = \Sigma_{t|t-1} - \Sigma_{t|t-1} \boldsymbol{\gamma}^{\mathsf{T}} \left(\boldsymbol{\gamma} \Sigma_{t|t-1} \boldsymbol{\gamma}^{\mathsf{T}} + N_t \right)^{-1} \boldsymbol{\gamma} \Sigma_{t|t-1} \,. \tag{A.44}$$

The one-step forward equation of (A.44) is

$$\Sigma_{t+1|t+1} = \Sigma_{t+1|t} - \Sigma_{t+1|t} \boldsymbol{\gamma}^{\mathsf{T}} \left(\boldsymbol{\gamma} \Sigma_{t+1|t} \boldsymbol{\gamma}^{\mathsf{T}} + N_{t+1} \right)^{-1} \boldsymbol{\gamma} \Sigma_{t+1|t} \,. \tag{A.45}$$

Substituting (A.38) for $\Sigma_{t+1|t}$ in (A.45) gives

$$\Sigma_{t+1|t+1} = \boldsymbol{\alpha}\Sigma_{t|t}\boldsymbol{\alpha}^{\mathsf{T}} + M_t - \left[\boldsymbol{\alpha}\Sigma_{t|t}\boldsymbol{\alpha}^{\mathsf{T}} + M_t\right]\boldsymbol{\gamma}^{\mathsf{T}}\left[\boldsymbol{\gamma}\left[\boldsymbol{\alpha}\Sigma_{t|t}\boldsymbol{\alpha}^{\mathsf{T}} + M_t\right]\boldsymbol{\gamma}^{\mathsf{T}} + N_{t+1}\right]^{-1}\boldsymbol{\gamma}\left[\boldsymbol{\alpha}\Sigma_{t|t}\boldsymbol{\alpha}^{\mathsf{T}} + M_t\right]. \quad \text{(A.46)}$$

Given $\Sigma_{t|t}$, Equation (A.46) generates $\Sigma_{t+1|t+1}$ recursively. Thus, Equation (A.46) reflects the evolution between the variance-covariance matrix at the current period t, $\Sigma_{t|t}$ and the variance-covariance matrix at the next period $t+1$, $\Sigma_{t+1|t+1}$, which is described as the transition equation for the variance of the net profitability for each technology in Chapter 3.

We have already derived the evolution of the mean of the net profitability in (A.35) and (A.36), but those equations have a component whose subscript is represented as $t+1|t$, $\Sigma_{t+1|t}$. As discussed above, it is necessary to consider $\Sigma_{t|t}$ ($\Sigma_{t+1|t+1}$) rather than $\Sigma_{t|t-1}$ ($\Sigma_{t+1|t}$) for simplicity. Thereby, we try to obtain the evolution between the subscript $t|t$ and the subscript $t+1|t+1$. First, we multiply $\boldsymbol{\gamma}^{\mathsf{T}}N_t^{-1}$ to both sides of the Equation (A.44).

$$\begin{aligned}
\Sigma_{t|t} \times \boldsymbol{\gamma}^{\mathsf{T}}N_t^{-1} &= \left[\Sigma_{t|t-1} - \Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}}\left(\boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}} + N_t\right)^{-1}\boldsymbol{\gamma}\Sigma_{t|t-1}\right] \times \boldsymbol{\gamma}^{\mathsf{T}}N_t^{-1} \\
&= \Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}}N_t^{-1} - \Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}}\left(\boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}} + N_t\right)^{-1}\boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}}N_t^{-1} \\
&= \Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}}\left[N_t^{-1} - \left(\boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}} + N_t\right)^{-1}\boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}}N_t^{-1}\right]. \qquad \text{(A.47)}
\end{aligned}$$

Second, the inverse matrix of N_t, N_t^{-1} can be considered as follows:

$$\begin{aligned}
N_t^{-1} &= I \cdot N_t^{-1} \\
&= \left[\boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}} + N_t\right]^{-1}\left[\boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}} + N_t\right]N_t^{-1} \\
&= \left[\boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}} + N_t\right]^{-1}\left[\boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}}N_t^{-1} + N_tN_t^{-1}\right] \\
&= \left[\boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}} + N_t\right]^{-1}\left[\boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}}N_t^{-1} + I\right]. \qquad \text{(A.48)}
\end{aligned}$$

Substituting (A.48) for the first N_t^{-1} in (A.47) results in

$$\Sigma_{t|t}\boldsymbol{\gamma}^{\mathsf{T}}N_t^{-1}=\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}}\left[\left[\boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}}+N_t\right]^{-1}\left[\boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}}N_t^{-1}+I\right]-\left(\boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}}+N_t\right)^{-1}\boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}}N_t^{-1}\right]$$

$$=\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}}\left[\left[\boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}}+N_t\right]^{-1}\left[\left[\boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}}N_t^{-1}+I-\boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}}N_t^{-1}\right]\right]\right]$$

$$=\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}}\left[\left[\boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}}+N_t\right]^{-1}\times I\right]$$

$$=\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}}\left[\boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}}+N_t\right]^{-1}. \tag{A.49}$$

Finally, (A.49) is introduced into (A.34) in terms of the Kalman-gain coefficient K_t

$$K_t=\Sigma_{t|t-1}\cdot\boldsymbol{\gamma}^{\mathsf{T}}\cdot\left\{\boldsymbol{\gamma}\Sigma_{t|t-1}\boldsymbol{\gamma}^{\mathsf{T}}+N_t\right\}^{-1}$$

$$=\Sigma_{t|t}\boldsymbol{\gamma}^{\mathsf{T}}N_t^{-1}. \tag{A.50}$$

Substituting (A.50) for K_t in (A.33) gives

$$\boldsymbol{\mu}_{t|t}=\left(I-K_t\boldsymbol{\gamma}\right)\boldsymbol{\alpha}\boldsymbol{\mu}_{t-1|t-1}+\left(I-K_t\boldsymbol{\gamma}\right)\boldsymbol{\beta}\mathbf{x}_{t-1}+\left(I-K_t\boldsymbol{\gamma}\right)\boldsymbol{\chi}\mathbf{y}_{t-1}+K_tz_t$$

$$=\left(I-\Sigma_{t|t}\boldsymbol{\gamma}^{\mathsf{T}}N_t^{-1}\boldsymbol{\gamma}\right)\boldsymbol{\alpha}\boldsymbol{\mu}_{t-1|t-1}+\left(I-\Sigma_{t|t}\boldsymbol{\gamma}^{\mathsf{T}}N_t^{-1}\boldsymbol{\gamma}\right)\boldsymbol{\beta}\mathbf{x}_{t-1}+\left(I-\Sigma_{t|t}\boldsymbol{\gamma}^{\mathsf{T}}N_t^{-1}\boldsymbol{\gamma}\right)\boldsymbol{\chi}\mathbf{y}_{t-1}+\Sigma_{t|t}\boldsymbol{\gamma}^{\mathsf{T}}N_t^{-1}z_t$$

$$=\left[I-\Sigma_{t|t}\boldsymbol{\gamma}^{\mathsf{T}}N_t^{-1}\boldsymbol{\gamma}\right]\left[\boldsymbol{\alpha}\boldsymbol{\mu}_{t-1|t-1}+\boldsymbol{\beta}\mathbf{x}_{t-1}+\boldsymbol{\chi}\mathbf{y}_{t-1}\right]+\Sigma_{t|t}\boldsymbol{\gamma}^{\mathsf{T}}N_t^{-1}z_t. \tag{A.51}$$

The one-step forward equation of (A.51) is

$$\boldsymbol{\mu}_{t+1|t+1}=\left[I-\Sigma_{t+1|t+1}\boldsymbol{\gamma}^{\mathsf{T}}N_{t+1}^{-1}\boldsymbol{\gamma}\right]\left[\boldsymbol{\alpha}\boldsymbol{\mu}_{t|t}+\boldsymbol{\beta}\mathbf{x}_t+\boldsymbol{\chi}\mathbf{y}_t\right]+\Sigma_{t+1|t+1}\boldsymbol{\gamma}^{\mathsf{T}}N_{t+1}^{-1}z_{t+1}. \tag{A.52}$$

Equation (A.52) reflects the evolution of the conditional mean of the net profitability given z_t for each technology as discussed in Chapter 3.[39]

In sum, given the system equation (A.1) and the measurement equation (A.2), both Equation (A.52) and Equation (A.46) constitute the Kalman filter algorithm, generating the

[39] Note that Chapter 3 doesn't consider farmers' strategic behavior with neighbors. Thereby $\boldsymbol{\chi}\mathbf{y}_t$ is dropped in Chapter 3.

linear least-squares estimates $\boldsymbol{\mu}_{t|t}$ and its corresponding error covariance matrix $\Sigma_{t|t}$ together in a recursive way. The Kalman filter algorithm reflects learning process of sufficient statistics (the mean and the variance of the net profitability given z_t for each technology) as discussed in Chapter 3. Note that individual learning and social learning are captured by the parameter vector $\boldsymbol{\gamma}$.

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