ADOPTION AND DIFFUSION OF AGROBIOTECHNOLOGIES IN THE US COTTON PRODUCTION

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by

PASU SUNTORNPITHUG

Dr. Nicholas Kalaitzandonakes, Dissertation Supervisor

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The undersigned, appointed by the Dean of the Graduate School,

have examined the dissertation entitled

ADOPTION AND DIFFUSION OF AGROBIO TECHNOLOGIES IN

THE US COTTON PRODUCTION

Presented by Pasu Suntornpithug

A candidate for the degree of Doctor of Philosophy

And thereby certify that in their opinion it is worthy of acceptance.

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Thomas G. Johnson
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DEDICATION

To my mother and father

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It is apparent that the completion of my dissertation would not have been possible without the kind support of numerous people. First and foremost, I would like to thank my father and mother, whose tireless, endless and unconditional love, encouragement, and support throughout my life, have made this work possible.

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Pasu Suntornpithug

Dr. Nicholas Kalaitzandonakes, Dissertation Supervisor

ABSTRACT

The study examines the farm level adoption and county level diffusion of three cotton biotechnologies in the US: insect resistant (Bollgard®), herbicide tolerance (Roundup Ready®), and stacked trait (Bollgard® & Roundup Ready®). Adoption and diffusion of these cotton biotechnologies are interdependent. A theoretical framework is developed to consider the adoption decision first. An optimal control model explains the effects of various learning mechanisms on the adoption of multiple, interdependent, and divisible innovations. Empirical specifications use a Generalized Method of Moments framework. Farmers are found to simultaneous adopt multiple technologies influenced by perceived economic gains, learning from own experience, and their neighbors' adoption. Other factors also influence adoption decision including: interdependencies among biotechnologies and certain agronomic practices (e.g. minimum tillage). Adoption is found to be scale neutral. Aggregate (county level) models confirm that potential economic gains, learning, innovation interdependencies and complementarities with agronomic practices drive the diffusion of the cotton biotechnologies.

CHAPTER 1

INTRODUCTION

Radical scientific discoveries can profoundly affect economic growth and social welfare (Romer, 1990). When radical discoveries link together and reinforce each other, they create a platform for continuing innovation that can affect multiple sectors of the economy and cause far-reaching socioeconomic and structural changes (Freeman and Perez, 1988).

Biotechnology is just such a platform innovation. Radical discoveries, such as gene transfer and cell fusion, marked the dawn of modern biotechnology in the early 1970s. Through further discoveries, biotechnology quickly emerged as a collection of diverse and reinforcing technologies with a wide range of applications in agriculture, forestry, food processing, waste management, pollution control, chemicals, raw materials, energy, cosmetics, pharmaceuticals, and other sectors (Altman, 1998).

In its early stages, agricultural biotechnology innovation progressed slowly as basic enabling technologies and a regulatory framework were being developed (Kalaitzandonakes and Bjornson, 1997). First-generation products began to arrive at the market in the mid-1990s, after almost twenty years of research and field experimentation. First-generation products have been, principally, crops with modified input traits, such as herbicide tolerance and resistance to particular insect pests. Other product introductions have included crops with resistance to fungal and viral diseases, biopesticides, yield-enhancing hormones for livestock, fruit with delayed ripening, flowers with altered colors, and enzymes for food processing. Second generation agrobiotechnologies are expected to arrive in the market over the next decade and include bioengineered crops with modified agronomic and output traits (Mazur, McElroy, 1999).

Unlike product development, the adoption of first-generation agricultural biotechnologies has been quite rapid. In 1996, less than 4 million acres in six countries were planted with insect resistant and herbicide tolerant crops. By 2003, worldwide adoption had expanded to over 160 million acres (James, 2003). For some countries, uptake of bioengineered crop varieties has been the fastest on record. And in a few cases (e.g. Brazil, Uruguay) adoption has been rapid even though it was illegal, as it lacked local regulatory clearance for plantings.

Interestingly, only modest research efforts have been devoted to understanding the unprecedented adoption and diffusion of first generation biotechnologies. Indeed, one can find only a handful of published studies that have formally modeled producer adoption decisions (as in Marra et al., 2001[b,c] and Kalaitzandonakes and Suntornpithug, 2001). Instead, there has been far more interest in measuring the environmental impacts of agrobiotechnologies (Clark & Kuiper, 2001; Cullum & Smith, 2001; Diamand, 1999; Edge et al., 2001; Ervin et al, 2000; Marshall, 1998; Nickson & Head, 1999; Renner, 1999), and their economic distribution both at the farm-level (e.g. see Marra for a review of farm-level impact assessment studies) and at an aggregate level (Falck-Zepeda, et al., 2000[a,b]; Traxler & Falck-Zepeda, 1999; Moschini, et al., 2000). Given the broad interest in the impacts of agrobiotechnologies, the lack of formal analysis of producer adoption behavior is curious. After all, unless the factors that shape adoption decisions are clearly understood, it is difficult to decide how impacts should be defined and measured (Kalaitzandonakes and Suntornpithug, 2003).

Beyond the rapid pace, other dimensions of agricultural biotechnology adoption and diffusion are also of interest. Simultaneous introduction of a number of traits for multiple crops have put various crop biotechnologies in a position to compete for land share, but also, potentially influence each others' adoption patterns (e.g. through cross-technology knowledge externalities). How might interdependencies among various biotechnologies affect each others' adoption and diffusion patterns? The answer to this question is unclear. Previous adoption (and impact assessment) studies (as in Carlson *et al.*, 1998; Fernandez-Cornejo *et al.*, 1999; Marra, 1999; and Marra *et al.,* 2001) have considered the uptake of agrobiotechnologies one at a time; that is, separately from the adoption of other agrobiotechnologies or related agronomic practices.

Many agricultural biotechnologies have also exhibited interesting diffusion patterns. Instead of the standard S-shaped paths that have been observed across various innovations and sectors in the past, many agricultural biotechnologies have had "zigzag" diffusion paths. Such paths suggest dis-adoption and reengagement. What factors explain such diffusion patterns then? Again, this question can not be adequately answered as there are no diffusion studies of agricultural biotechnologies.

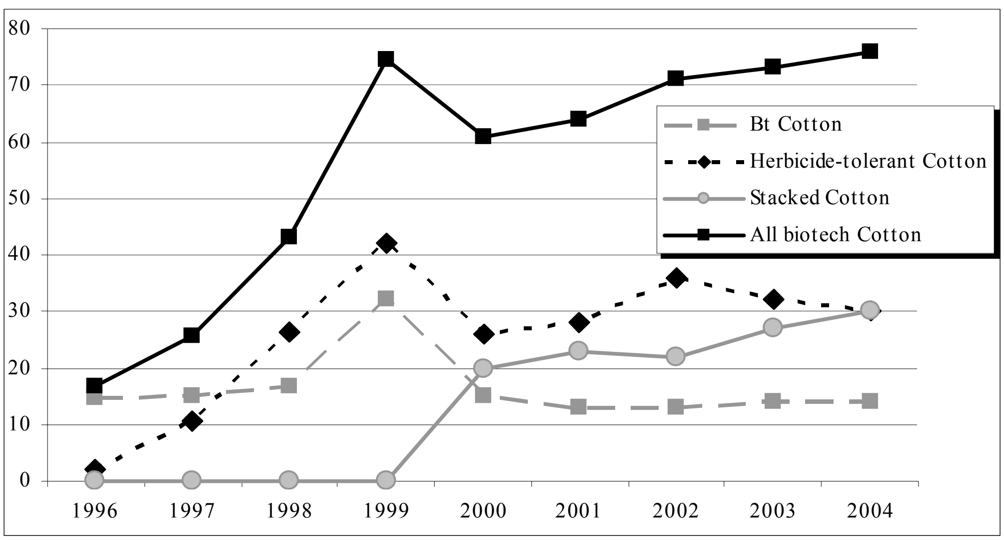
To answer these and other related questions, I first develop a theoretical model of producer adoption behavior. I then empirically test its relevance in adequately explaining adoption and diffusion patterns for a set of biotechnologies in US cotton production. Adoption and diffusion of the selected cotton biotechnologies display rapid rates, potential interdependencies, and in some cases, unconventional diffusion paths. In this context, they present an interesting case study. A basic overview of these biotechnologies is presented next.

Overview of Cotton Biotechnologies

Prior to the introduction of agricultural biotechnologies, pest management relied exclusively on use of synthetic insecticides, as well as, herbicides and conventional tillage practices to control harmful insects and weeds. Conventional pest control practices require substantial amounts of labor, capital, and management prior, during, and after planting. Precise tank mixes and identification of suitable application windows complicate conventional pest control methods. Pest resistance to pesticides, crop injury, high production costs, and, occasionally, negative health and environmental externalities pose additional challenges. Consequently, there have been ongoing efforts to develop alternative pest control methods.

No crop has had a more pronounced need for an alternative to conventional pest control methods than cotton. Historically, conventional cotton production has relied heavily on chemical pesticides, using about 25% of all the agricultural pesticides used worldwide. Some of these pesticides have been among the most toxic agricultural chemicals, starting with chlorinated hydrocarbons (such as DDT), which were banned in the 1970s and 1980s because of their high toxicity. Next came organophosphates, many of which were also highly toxic. Pyrethroids were widely used in 1980s and 1990s. However, pest resistance to organophosphates and pyrethoids developed soon after their introduction in many cotton producing regions.

In this environment, four different cotton biotechnologies were introduced in the market in the mid-1990s. The three most dominant technologies --Bollgard®, Roundup Ready®, and stacked Bollgard®/Roundup Ready® --are considered here.[1] Collectively, these three technologies were used on almost 80% of the US cotton acres cultivated in 2004 (figure 1).



The Adoption of Bollgard® Cotton

Bollgard® (BG) cotton has been engineered to resist insect pests and was introduced in the market in 1996. Insect resistance has been engineered through the use of a gene from the common soil bacterium *Bacillus thuringiensis (Bt),* which when inserted into cotton

[1] BXN cotton, which is resistant to the herbicide bromoxynil, was introduced to the US cotton market in 1995. Adoption of BXN cotton is limited by a restriction on the amount of cotton acres that can be treated with bromoxynil. Because the BXN technology cannot grow beyond its current 4% of US cotton acreage, its adoption is not considered here.

plants, causes them to produce a protein that is toxic to lepidoptera insect pests. *Bt* cotton is effective in controlling caterpillar pests such as cotton bollworm (*Helicoverpa zea)* and pink bollworm (*Pectinophora gossypiella)*, and is partially effective in controlling tobacco budworm (*Heliothis virescens)* and fall armyworm (*Spodoptera frugiperda)*.

Use of BG cotton in the US has been associated with meaningful reductions in the number of sprays for Lepidoptera pests (Carpenter and Giannesi, 2000, Edge et al., 2001, Heimlich et al., 2000). Fewer applications may translate into lower quantities of synthetic pesticides and associated expenses. Fewer sprays may also translate into meaningful labor and capital savings, as less labor and machinery hours may be necessary for mixing and spraying (ReJesus et al., 1997).

Potential cost efficiencies may be strengthened by more effective pest control relative to that achieved through conventional varieties. BG varieties have been shown to provide effective protection against target pests (Edge et al., 2001). Their relative effectiveness may also improve as the efficacy of conventional pest control methods depreciates through insect resistance buildup (Marra et al., 2001; and also Pray and Huang, 2003; and Traxler et al., 2003). Furthermore, reduced damage on beneficial insects can improve secondary control over non-target pests (Edge et al., 2001).

Pest damage is stochastic, influenced by the levels of pest populations and weather conditions. To prevent major infestations, cotton growers make complex decisions before and during the growing season (e.g., scouting, choosing appropriate insecticides, and choosing the timing of application). Use of BG cotton may reduce the risk of unpredictable outbreaks as it provides continuous protection, and could act as insurance (Carpenter and Giannesi, 2000). Similarly, use of BG cotton can temper uncertainties associated with weather interfering with, or negating, ill-timed applications for key pests. Hence, the use of BG cotton may reduce production risk and increase yields.

Synergies with certain agronomic practices might also exist. For instance, use of BG cotton may increase the productivity of irrigation. Synthetic pesticide applications tend to interrupt watering and interfere with efficient use of irrigation systems. Accordingly, producers who use irrigation may be more inclined to adopt BG technology as a way of improving the efficiency of their irrigation programs.

Adoption of Roundup Ready Cotton

Roundup Ready® (RR) cotton varieties have been engineered to resist the herbicide glyphosate[2], which effectively controls a wide range of grasses and broadleaf weeds. The RR technology was introduced in the market in 1997.

Use of herbicide resistant cotton has allowed the substitution of low-priced glyphosate for more expensive selective post-emergence herbicides and, in some cases fewer herbicide applications (Carpenter, 2002; Carpenter and Giannesi, 2001; Heimlich et al., 2000). As with BG cotton, a reduced number of sprays can lead to lower herbicide costs, as well as, lower labor and equipment costs. Further cost efficiencies may be possible from savings in management efforts. Herbicide programs using selective post-emergence herbicides can be complex. Producers must scout the fields, correctly identify the type and size of weeds that must be controlled, and decide on an appropriate program by mixing relevant selective herbicides. All such activities require specialized knowledge

[2] *Glyphosate* is essentially a phosphorus containing form of the nonessential amino acid, *glycine*.

and managerial time. With an effective non-selective herbicide, such as glyphosate, less management may be required.

Use of RR cotton may also reduce production risk. Selective post-emergence herbicides can control specific weeds while they are in early phases of growth. Only a narrow window is therefore available for their effective use. Excessive rainfall may keep equipment off the field until weeds are too mature to control. With RR cotton, the potential window for spraying is extended, as glyphosate controls larger weeds well. Accordingly, production risk and associated output losses may be reduced.

Potential synergies between RR cotton and certain agronomic practices may also exist. The most notable example is the increased ease of implementing no-till or minimum tillage programs in RR cotton acres (Carpenter and Giannesi, 2000). Producers may also find ultra narrow row cultivation systems increasingly profitable with more effective early season burndown. The decreased need of machinery for controlling post-emergence weeds may allow areas between rows to be reduced to a few inches, resulting in more efficient land use. As in the case of BG technology, use of RR technology may also improve the efficiency of irrigation programs.

Stacked Bollgard®/Roundup Ready® Cotton

Stacked Bollgard®/Roundup Ready® (ST) cotton varieties were introduced in 1998 to combine the properties of BG and RR technologies. The two technologies are employed for different purposes but may find application in the same fields. Hence, producers can evaluate the economics of single traits independently or as a bundle. The use of stacked traits is most likely to occur in areas with high concentrations of budworms and bollworms, as well as broadleaves and grasses.

Perceptions of Innovation Advantages and Adoption Decisions

The potential technical and economic advantages offered by the three cotton biotechnologies are expected to directly influence the adoption decisions of producers. In their efforts to maximize profits, cotton producers may adopt BG, RR, or ST cotton in order to reduce production costs, ease production risks and associated output losses, and exploit potential synergies with other agronomic practices. Adoption decisions for these three agrobiotechnologies, however, are not independent. In most cases, the individual technologies readily substitute for one another. For instance, single trait and stacked technologies may be close substitutes given their overlapping pesticidal activities. Within this context, the adoption decision of one cotton biotechnology might directly influence the adoption decision of another.

Similarly, complementarities between BG, RR, and ST with certain agronomic practices may imply further interdependencies. For instance, use of herbicide resistant technologies may improve the economics of minimum tillage and strengthen its adoption. Increased adoption of minimum tillage could simultaneously encourage adoption of RR and ST technologies in cotton production.

As producer adoption decisions become more interdependent, complexity increases and uncertainties about the long term profitability of these biotechnologies could emerge. All the potential technical advantages of agrobiotechnologies are stochastic in nature, as they are critically influenced by the actual levels of pest infestations and by weather. It is up to the producers to separate “noise” from potential.

Producers must therefore weigh the potential technical and economic advantages of agrobiotechnologies in the face of significant uncertainty and against up-front extra costs (e.g., more expensive seeds and licensing fees for the technologies). Under uncertain conditions, producers could choose to partially adopt such technologies to slowly evaluate their performance (Abadi Gadim and Pannell, 1999, Cameron, 1999; Kalaitzandonakes and Boggess, 1993, Marra et al., 2001). Over time and through learning by doing or learning from other users, producers could sharpen their expectations about the profitability of the three technologies and gain knowledge on how to optimize their use, both agronomically and economically.

Research Questions and Hypotheses

Against this context, one can pose several relevant research questions:

- What is the relative importance of perceived economic gains from cotton biotechnology innovations on their adoption and diffusion?
- What kind of learning mechanisms do farmers use to optimize their adoption decisions?
- How much of an impact does learning have on producer decisions? How do interdependencies among cotton biotechnologies and other agronomic practices affect producer adoption decisions?

- Are cotton biotechnologies scale biased?
- Can the factors that explain producer adoption decisions also explain observed diffusion patterns and innovation dynamics for cotton biotechnologies?

To answer these and other related questions, I develop a theoretical model of producer adoption decisions and propose the following hypotheses:

Hypothesis 1

US cotton producers adopt biotechnologies in order to maximize an expected stream of profits over a given period of time. Accordingly, producer adoption decisions are closely influenced by perceived economic gains from various biotechnologies.

Hypothesis 2

US cotton producers account for interdependencies and choose bundles of conventional technologies, agricultural biotechnologies and relevant agronomic practices. Hence, their behavior is characterized by multiple simultaneous and interdependent adoption decisions.

Hypotheses 3

In the presence of complexity and uncertain performance, US cotton producers use multiple learning mechanisms to optimize the use of the three cotton biotechnologies over time. They partially adopt one or more of the technologies and learn by doing. They also learn by observing other users. Hence, their adoption decisions are dynamic in nature.

Hypothesis 4

Cotton biotechnologies are highly divisible and require no significant upfront investment. Their adoption implies no scale bias and it is evenly distributed across all firm sizes.

Hypothesis 5

Dynamic and simultaneous considerations explain not only adoption decisions among producers in any given year but also aggregate diffusion patterns observed over a period of time.

I empirically test these hypotheses within the context of two closely linked but separate adoption and diffusion models for the selected cotton biotechnologies. For the adoption model, I use detailed survey data for a representative sample of US producers to examine the influence of the following factors: perceived innovation benefits, technology interdependencies, and learning from past decisions-- whether to adopt and to what extent among the three technologies. For the diffusion model, I examine the influence of the same variables on the whole population of adopters over multiple years.

Study Outline

The remaining of the study is structured as follows: In chapter 2, I review relevant literature on adoption and diffusion of agricultural innovation and specifically of agrobiotechnologies. In chapter 3, I develop a theoretical optimal control model in order to examine the dynamic effects of various learning mechanisms on the adoption of multiple, interdependent, and divisible innovations.

The complexity of the theoretical framework emphasizes the importance of the empirical models developed in chapter 4 and 5. Indeed the empirical adoption model presented in chapter 4 and the empirical diffusion model presented in chapter 5 examine the impacts of the following factors: perceived economic gains, learning mechanisms, interdependencies of multiple technologies and agronomic practices. Perceived economic gains include perceived pest control effectiveness, convenience, risk consideration, and perceived cost savings. Learning mechanisms include learning by doing from exact as well as that from similar technologies, and learning from others. Interdependencies include all possible substitutability among cotton varieties (traditional and biotech cotton) and synergies with agronomic practices. These interdependencies are simultaneous and dynamic. The Generalized Method of Moments (GMM)[3] is used to estimate coefficients in a system of adoption and diffusion equations.

Finally, in chapter 6, I summarize the key finding of the study and profice some concluding comments.

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[3] Inexperience readers would benefit from the following references: Johnston and John (1997), Maddala (1992), Mullen (2003)[a,b,c], Pindyck and Rubinsfield (1998)

CHAPTER 2

INNOVATION ADOPTION AND DIFFUSION: A LITERATURE REVIEW

Adoption and diffusion are related but distinct concepts, with the later being a measure of aggregate adoption. There is a vast literature that examines the patterns and determinants of innovation adoption and diffusion. In this area, Roger's pioneering work provided a basic framework for many studies that followed in the last 40 years. Roger introduced theories that explained innovation adoption and diffusion. These theories have been organized as: 1) perceived attributes theory, 2) innovation decision process theory, 3) individual innovativeness theory, and 4) rate of adoption theory (Rogers, 1995.)

All four theories are linked to one another. Perceived attributes theory focuses on the characteristics of the innovation that affect its rate of adoption. The innovation decision process theory and the individual innovativeness theory deal with the adopt/not adopt decision of the individual innovator and the innovators characteristics. Finally, the rate of adoption theory examines the temporal evolution of adoption and diffusion.

The characteristics of an innovation matter. Rogers explained that innovations are adopted at faster rates when they possess some of the following characteristics: trialability, observability, a clear relative advantage against incumbent technologies, simplicity, and compatibility with existing infrastructure, knowledge and other assets.

When considering such dimensions, potential adopters go through five stages in their decision process. These stages include: knowledge –where they increase their awareness of the innovation and its characteristics; persuasion –where they develop an attitude, favorable or unfavorable, towards the innovation; decision –where they engage in activities that lead to adoption or rejection; implementation –where they carry out their adoption/non adoption decision; and confirmation –where they look for reinforcement that the correct decision was made regarding the adoption.

Roger went on to explain in his individual innovativeness theory that individuals differ in their propensity to innovate with some being more predisposed to innovate than others. He used a bell shaped normal distribution to categorize individuals into five categories: innovators (venturesome), early adopters (respectable), early majority (deliberate), late majority (skeptical), and laggards (traditional).

Roger also proposed that the rates at which innovations are diffused over time yield predictable patterns that resemble an *S-shaped* curve. The rate of adoption accounts for the number of cumulative adopters and theorizes that an innovation goes through a period of slow, gradual growth before experiencing a period of relatively dramatic and rapid growth; then the innovation's rate of adoption gradually stabilizes and eventually declines.

Most studies of agricultural innovations in the past forty years have confirmed many essential elements of Roger's theories. The characteristics of the innovation have been found to matter. For instance, agricultural innovations can be categorized as divisible or non-divisible (lumpy). Non-divisible innovations involve dichotomous adoption decision, while divisible innovations allow for partial adoption.

The majority of adoption studies have treated agricultural innovation as non-divisible though exceptions exist (e.g. Cameron, 1999; Marra et al, 2001a; Zhang *et al*., 2002). Data limitations have usually been responsible for such a strong assumption.

Adoption behavior and adoption rates in the case of divisible innovations can be very different from non-divisible ones. Non-divisible innovations often require lumpy upfront investments that can become sunk costs. Such costs imply economies of scale and hence a scale bias might be present among adopters. Divisible technologies are typically more scale neutral as they require less upfront and lumpy investment. Furthermore, they allow for partial adoption and experimentation (or trialability) as well as easier reversal of adoption.

Similarly, many adoption studies of agricultural innovations have focused on the heterogeneity of agricultural populations and their differential propensity to adopt – especially in developing countries (Arellanes and David, 2003; Besley and Case , 1996; Cameron, 1999; Godoy *et al.,* 2000; Just and Ziberman, 1983; Smale and Heisey, 1993; Thirtle *et al.,* 2003). Education and other human capital variables have frequently been used as indicators of population heterogeneity and propensity to adopt (Abidi Ghadim and Pannell, 1999; Hubbell *et al.,* 2000; Godoy *et al.,* 2000). A large number of studies have also treated informational asymmetries as the key source of heterogeneity in agricultural populations and differential adoption behaviors (Leathers and Smale, 2001; Marra and Hubbell, 2001; Shampine, 1998). Within this context they have focused particularly on the importance of information that increases producer awareness of the innovations and their virtues (e.g. extension, other adopters –Bala and Goyal, 1998; Ellison and Fudenberg, 1993; Foster and Rosenzweig, 1995; Zhang *et al.,* 2002) and on producer attitudes.

Finally, there have been a number of agricultural diffusion studies that have examined the temporal path of aggregate adoption (e.g. McWilliams and Zilberman, 1996; Zhang, 2000). Griliches' classic hybrid corn diffusion study was a picture-perfect case of an S-shaped diffusion path, much like that suggested by Roger.

Some prior adoption and diffusions studies of agricultural and other innovations have particular importance to this study and for that reason I review them in more detail below.

Learning and Innovation Adoption

Learning mechanisms, information, and risk

Learning and innovation adoption and diffusion are interdependent (Abadi Ghadim, 1999; Bala, 1998; Cameron, 1999; Ellison & Fudenberg 1993, Feder et all., 1985; Foster & Rosenzweig, 1995; Marra et al., 2001ab; McWilliams & Zilberman, 1996; Plourabour et al., 1998; Zhang et al., 2002).

Typical learning mechanisms involve learning by doing (experience), learning from neighbors (imitation), and learning from other external sources. Learning by doing describes all productivity improvements as users learn how to better utilize an innovation over time. Ellison and Fudenberg (1993) argued that economic agents also learn and base their adoption decisions on the experience of their neighbors, a process they called "social learning". They assumed that economic agents observed their neighbors' choices and payoffs, and periodically re-evaluated their own adoption decisions. However, the circumstances of their neighbors were assumed sufficiently heterogeneous so that economic agents would not make the same choice even with full information.

Ellison and Fudenberg (1993) constructed mathematically two theoretical models of social learning: one in which the same technology was optimal for all agents and another in which the new technology was better for some of them.

The first model, called "homogenous-population model," assumed that two competing technologies were available to economic agents in such a way that some fraction of them had the opportunity to revise their choices while others did not have such an opportunity and had to continue using whichever technology they had previously used. This model began with a "naive-rule of thumb" in which players ignored all historical data except those of superior technologies in the previous period. Under these conditions, players tended to choose the more popular technology even if profits were lower in previous periods (so called "popular weighting"). In the long run, this led agents to adopt and stick with better technologies. Presumably, relative popularity can serve as a proxy of historical performance. The homogenous-population model predicted the speed of new technology adoption was correlated with the extent of payoff difference, and the combination of inertia and popularity weighting led to efficient long run behavior.

The second model, called the "heterogeneous-population model," attempted to answer the question of whether the new technology was adopted by the appropriate agents. It was assumed that agents based their adoption decisions on the relative performance of the new and old technologies at nearby locations which the authors called "within one window width" of their own. This was crucial since Ellison and, Fudenberg perceived that agents could not observe outcomes at faraway locations and, when they could, the characteristics of remote locations were different enough to be considered irrelevant in the agents' decisions. This window width concept was exogenous in the model and a proxy of the neighbor-influence concept that has been described in various adoption studies. The heterogeneous-population model predicted that small window widths and high popularity weights caused slow diffusion.

Various combinations of learning mechanisms have been modeled in previous agricultural innovation adoption studies. For instance, learning by doing and learning from neighbors have been investigated by Foster and Rosenzweig (1995), Kalaitzandonakes and Suntornpithug (2001, 2003), and Tsur et al. (1990). Learning by doing has been included in Abadi Ghadim & Pannell (1999), Cameron (1999), and Leathers & Smale (1991). Learning from neighbors alone has been included in Bala and Goyal (1998), Ellison and Fudenburg (1983), Karshenas et al (1993), Marra et al., (2001a).

Risks and uncertainties are closely related to learning mechanisms in adoption studies. Over time, risk and uncertainties are minimized upon accumulation of information through the learning process. Bayesian learning (Feder and O'Mara, 1982) or ad hoc learning rules are usually employed to take into account the distribution of uncertainties. Potential adopters are either assumed risk neutral (Leathers and Smale 1991; McWilliams and Zilberman, 1996) or risk averse (Just & Zilberman, 1983; Tsur et al, 1990).

Since adopters can gather information from many sources including own experience, neighbors, media, and other external sources, the quality of information becomes important and variable. Quality of information is assumed to vary across sources and along the adoption cycle (Marra, 2001a). Own experience and early successful adopters have been found to be responsible for the most useful information

(Foster and Rosenzweig, 1995; Zhang *et al.*, 2002). Fischer, Arnold, and Gibbs (1996) have pointed out that the value of any new piece of information is lower when it is correlated with those previously obtained.

The Role of Learning on the Adoption of Single and Bundled Innovations

Adoption of potentially interdependent innovations is of interest to this study. Given the significance of learning to the adoption literature, I review here some key studies that have modeled various learning mechanisms for single innovations and bundles of interdependent innovations.

Adoption of Single Innovations

Abadi Ghadim and Pannell (1999) presented a conceptual framework of individual farmers' decisions on adoption of a single new technology. They modeled the adoption decision as a dynamic process spanning several years. Their framework allowed for learning by doing and accounted for a farmer's perceptions, managerial skills, and risk preferences.

This conceptual framework was empirically implemented by Abadi Ghadim in 2000. His study involved a three-year series of personal interviews with 130 crops producers in Western Australia where he collected actual and planned adoption behavior for a new crop, chickpeas. He used three limited dependent variable models, Tobit, Probit, and Heckman, for his empirical estimation and concluded that risk aversion and the relative riskiness of the innovation strongly impacted the adoption decision.

Marra, Pannell, and Abadi Ghadim (2001) revisited the influence of risk, uncertainties, and learning on the adoption of agricultural technologies. They concluded that to effectively understand an adoption decision, it was important to explicitly account for the farmers' perceptions about the riskiness of a technology, farmers' attitudes to risk, the role of experimentation and learning in reducing the perceived risk, and the option value of delaying adoption.

Cameron (1999) also studied the adoption decisions of farmers for high yielding seeds. Cameron measured the impact of learning by doing as the average profit differential between the new and the old seed experienced by the farmer and found this index to fit the data better than the commonly used learning by doing proxy of lagged profit differential. Cameron did not incorporate learning from others in his study due to data limitations. Cameron suggested then that any model that depends on learning by doing alone and does not incorporate learning from others has difficulties explaining why some farmers are late adopters. Cameron then pointed to the need to control for unobserved producer heterogeneity. Unobserved heterogeneity may include farm characteristics (e.g. land quality), unobserved farmer skills, initial beliefs of crop profitability, and so on. The author used fixed-effect dummy variables along with the method of instrumental variables to control for unobserved household heterogeneity and removed bias. Using panel data in a dynamic learning process proved to be superior to that of cross sectional data, which may suffer from omitted variable bias.

Foster and Rosenzweig (1995) investigated the impacts of learning by doing and learning from neighbors in the adoption of agricultural innovations using a modified target-input model. They used 4,118 surveyed household-level panel data (within 250 villages) from national representative samples of rural India on high-yielding-seed varieties (HYVs) between 1968 and 1971. Their own HYV experience variables included lagged cumulative HYV use by year for each farmer. The neighbor HYV experience variables included the lagged sum of hectares cultivated under HYV averaged over all sampled farmers in each village, whether excluding the respondent farmer. Several empirical models were estimated with and without HYV including OLS, fixed effect, standard instrumental variables fixed-effects, nonlinear instrumental variables fixed-effects, and constrained instrumental variable fixed effects.

The explanatory variables included farm equipment, farm animals, and irrigation assets of both the potential adopters and their neighbors. Foster and Rosenzweig (1995) concluded the imperfect knowledge about how to use new varieties was a significant barrier to adoption; however, as experience increased, the barrier diminished. Moreover, farmers with experienced neighbors were more profitable than those with inexperienced ones. Finally, farmers tended to free ride on the learning of others to minimize their losses by relying on their neighbors' knowledge to gain the relevant experience and then increase the use of new technology when it became more profitable.

Marra, Hubbell, and Carlson (2001) investigated the influence of information quality and learning, along with other variables of farm and farmer characteristics, on biotech cotton adoption in the Southeast US. Their study's arguments were based upon effective information hypothesis and popular weighting hypothesis. Marra et al., argued that farmers received information about the innovation from other users. They assumed that since neighbors lived close by and tended to have similar farm characteristics, the information about the innovation would tend to flow easier and be more relevant to them than others who live farther. However, early in the innovation cycle, the numbers of nearby adopters were low, so farmers would tend to gather more information from a larger group of users who lived farther away. In each stage of the adoption process, farmers weighted their adoption decision based on several sources of information, which differed in quality and reliability. Farmers learned to evaluate the performance of conventional and biotech cotton from both their own experience (learning by doing) and that of their neighbors, or other adopters, who were located further away, if their experiences could be gathered (learning from others). Mean differences in yields and profits between conventional and *Bt* cotton varieties were used to operationalize their hypotheses.

Their empirical research was based on the data collected in 1996 and included farmers from North Carolina, South Carolina, Georgia, and Alabama. Since the dependent variable involves binary choice (adopt/not adopt in 1996 and 1997), a probit model was used to estimate the influence of differences in perceived profitability, abilities, farm and farmer characteristics.

Marra et al., concluded that farm size and human capital had a significant positive effect on propensity to adopt; farmer education was positively related to the propensity to adopt; cotton growing experience did not have a significant impact on adoption propensity; own experience with the new technology, when available, had the most weight in the decision to adopt, otherwise county and state averages of yields and popularity (% state and % county biotech acres) were most important.

Sequential Adoption of Innovations

Leathers and Smale (1991) used a dynamic Bayesian model to explain sequential adoption when farmers were risk neutral. Farmers were assumed to maximize expected utility of income, which was a function of a decision set of technologies whose returns were conditional on the validity of information provided through extension reports. At a given time, although expected profits may be maximized by adopting the innovation package, expected utility could be maximized by adopting one or more components.

Their findings indicated that farmers, with similar characteristics but different prior judgments about the reliability of the extension reports, could choose to adopt different components of the innovation package. Accordingly, their model explained why farmers facing the same economic and agronomic conditions chose different adoption paths. Since uncertainties were reduced through experience, farmers could choose to adopt a component of the package rather than the complete package.

Adoption of Innovation Bundles

Feder (1982) examined a case where farmers encountered the choice between divisible technologies (crop varieties) and a lumpy technology requiring an upfront investment (a tube well). The potential yields of the modern crop varieties were higher if both technologies were adopted together. The adoption of lumpy technology also influenced the perceived risk associated with divisible technologies. Farmers were assumed to maximize their expected utility through both a dichotomous choice of whether lumpy technology should be adopted or not, and a proportional choice of intensity level for the divisible technology. The model implied that initially larger farms adopted both technologies whereas smaller farms adopted the divisible technologies to a limited extent. Smaller farms, however, would increase adoption of divisible technologies over time and eventually, many of them adopted the lumpy technology. This behavior can be explained by the fact that the optimal farm size threshold declined as uncertainty from perceived output variability decreased; over time perceived output variance associated with new divisible technology could decline as a result of learning by doing or better dissemination of information.

Dorfman (1996) studied adoption of multiple technologies using a multinomial probit (MNP) model that evaluated 625 apple growers' adoption of four technological bundles. The bundles involved combinations of two technologies: integrated pest management (IPM) and improved irrigation. Hence, four technology bundles were considered: no new technology, IPM only, improved irrigation only, both IPM and improved irrigation. The study utilized *Fruit and Nut Chemical Use Survey* data conducted by National Agricultural Statistics Service (NASS), and examined the influence of the operators' years of experience, amount of labor used in production, off-farm labor hours, operators' education level, acres planted, average age of the trees, planning density, and percentage of harvest sold for the fresh market on farmers' adoption decisions. Due to data limitations, price variables could not be included in the empirical adoption model. Estimation was done in a Bayesian framework, employing Gibbs sampling to circumvent past difficulties normally encountered in maximum likelihood estimation of MNP model. The results showed that farm size did not have a clear impact on adoption as anticipated. Off-farm labor was found to have a significant impact, suggesting the potential relevance of labor constraints and desirability of labor substitutability in the adoption process. An interesting insight from the study pointed to the fact that the negative covariance between adoptions of integrated pest management and improved irrigation implied crossed adoptions were often not optimal.

Heterogeneity among Adopters

While inherent economic advantages and learning are key to explaining the extent and rate of technology adoption, most studies have acknowledged that heterogeneity among firms and farm operators can often explain why all farmers may not adopt an innovation in the either short or long run (Fernandez-Cornejo & McBride, 2002). A number of characteristic differences among potential adopters have been modeled in various studies. Frequently, proxies for farm and farmer characteristics include farm size, yield, education, land tenure, access to information and credit, and location specific factors (e.g. cropping systems, climate, institutions, etc.).

Firm size is probably the most popular explanatory variable in adoption studies (Feder et al., 1985). Firm size has showed significance across a broad range of studies, particularly those with relatively high sunk costs. Hence, many innovations are scale biased as larger firms have demonstrated an advantage to acquiring more information or enjoying larger static benefits (Feder and Scale, 1984, McWilliams & Zilberman, 1996). Since education encourages firms to better process complex information, as does size, education and firm size have typically had positive relationships and have contributed to scale bias.

Feder and Umali (1993) concluded that factors such as farm size, credit, land tenure, and education may only be temporarily relevant. They empirically found that such factors were critical determinants in the initial phases of adoption of Green Revolution technologies but faded into insignificance in the later stages of the diffusion cycle.

Other studies have shown that certain technologies, especially divisible ones, are scale neutral with regard to both speed of adoption and per hectare benefits. For instance, biotech cotton technologies have been found to benefit small and large farmers equally (FAO, 2004; Kalaitzandonakes and Suntornpithug, 2003). In fact, Qaim and Zilberman (2003) argued that the relative performance of biotech cotton is likely to be greatest when used by small farmers in developing countries where severe infestation level and ineffective chemical pest control caused considerable yield losses. Their argument has so far been supported from studies in Argentina, China, and India.

Innovation Diffusion

When the level of adoption of a specific new technology is aggregated across a given population, adoption becomes diffusion. Details on innovation diffusion theories and reviews of empirical works can be found in Baptista (1999), Mahajan and Peterson (1985), and Rogers (1995). Geographers have added a spatial dimension to innovation diffusion process and relevant empirical concepts can be found in Baptista (2000) and Gardner et al. (1989).

Innovation diffusion is a slow process. Four different types of economic theories explain such delays and observed patterns of innovation diffusion (Baptista, 2000;

Choirat & Seri, 2003; Colombo & Mosconi, 1995; Karshenas & Stoneman, 1993). One of these theories relies on information asymmetries, whereas, the other three assume perfect information regarding the existence and nature of new technologies.

"Epidemic" effects are closely related to endogenous learning and describe a process of auto-propagation of the information on an innovation and transmission through contact among potential adopters. Hence, epidemic theories of diffusion present a disequilibrium approach caused by information asymmetries between potential users.

So called "rank" (or heterogeneity) effects have been used to explain the delay in adoption and diffusion. Given the heterogeneity of firms, differences in various characteristics can affect adoption probability, independently of behavior. Potential users of a new technology differ from each other in some important dimensions (inherent characteristics such as firm size). As a result of such heterogeneity, some firms obtain a greater return from the new technology than others, and consequently, adopt faster.

"Stock" effects have originated from game-theoretic models of adoption and diffusion. They typically hypothesize that the benefit to the marginal adopter from adoption declines as the number of previous adopters increases. Thus, for a given cost of adoption, there is a point in time when the number of total adopters makes adoption for the remaining firms unprofitable. This occurs even if the potential adopters are perfectly homogeneous. So, while epidemic and rank effects are based on the presence of differences among firms, stock effects can emerge in a perfectly homogenous environment. For instance, given Cournot oligopolistic behavior, the adoption of the new technology can reduce production costs and induce an increase in the optimal firm size, thereby leading to the reduction in the profitability for the future adopters.

"Order" effects are assumed to emerge from a first-mover advantage enjoyed by early adopters (e.g. because of the possibility of preemption on resources critical for the use of the technology such as prime geographic site or access to a pool of skilled labor). For a given cost of acquisition, it may be profitable only for some early adopters to adopt. The cost of acquisition was assumed to fall over time, so the number of adopters can rise. While both stock and order effects imply that the profitability of adoption declines as the number of adopter increases, stock effects imply an equilibrium number of adopters and lower profitability of adoption, order effects emphasize anticipation of subsequent adoptions; thus, order effects are found to have positive effects on adoption. This distinction determined the choice of variables entering to capture stock and order effects in the model.

Empirical applications of diffusion models have mostly focused on disequilibrium epidemic models. For instance, Bass' work was an early popular application in that it has been widely replicated in marketing and other fields. Bass' model has its origin in epidemiology and its generic form is given by:

$$\frac{dN(t)}{dt} = p[m - N(t) + \frac{q}{m} N(t)[m - N(t)]\,\mathrm{s}$$

where *N(t)* is the cumulative number of adopters at time *t, m* is the size of the potential adopters, *p* is the coefficient of innovation, and *q* is the coefficient of imitation. Other similar epidemic models of innovation diffusion also exist.

Epidemic modeling considers diffusion as a result of direct contact among adopters and potential ones. Information about the innovation is thought to spread like a disease. In their simplest form, epidemic models assume that a potential adopter will adopt the innovation upon learning of its existence and that information on the innovation is spread through direct contact. Through time, more potential adopters will utilize the innovation and the proportion of users in the industry will increase. Through the use of basic aggregate data on adopters at any given time *t*, various parameters of interest such as the speed of diffusion, the potential population of adopters and others can be estimated through a simple model and integration of a basic differential equation. The ability to generate standard S-shape diffusion curves has added to their attraction over the years.

Although use of such models in estimating and testing the existence of an *S*-shape curve has been extensive, such models are limited in some significant ways. First, epidemic models do not allow for dis-adoption. Second, they do not explain the adoption decision process and when might information be sufficient to induce adoption. Third, they do not provide for any other mechanisms of learning (beyond contact). In this way, they ignore other information channels (e.g. mass media) and active information gathering by potential adopters. A number of other limitations have also been pointed out including its embedded assumptions of homogeneous potential adopters and fixed innovation profits. Homogeneity of potential adopters and constant profitability from adoption has been broadly rejected in empirical adoption studies. In addition to these limiting assumptions, the standard epidemic diffusion model cannot explain why some firms adopt earlier than others.

So while epidemic models explicitly account for the role of information and learning in diffusion, they are naïve in their approach. Various studies have tried to correct the deficiencies discussed above. For example, the process of decision making under uncertainty has been further elaborated using Bayesian theory. Similarly, equilibrium models have been developed focusing on the decision process of the individual firms while assuming that information and knowledge of the innovation in the economy are unevenly distributed. Heterogeneity of potential adopters results in differences in adoption timing. Other extensions have accounted for the fact that the innovation might improve over time. The assumption of free information has also been relaxed to assume that information is specific, rare, and costly.

Innovation diffusion paths have also been produced through modeling in game theory as strategic interaction. This approach shows that even under very simple assumptions (identical adopters and no uncertainties), a firm may not adopt an innovation instantly, but sequentially. Nash equilibrium sometimes emerges when each firm adopts at different dates, even though all firms share the same perfect information. Game theoretic framework can also be extended to include the existence of learning and informational externalities since the game itself allows players to observe other players' payoff and react in such a way that takes into account others actions. While all such advances through equilibrium models offer useful insights, equilibrium models have been rarely empirically implemented.

Feder and Umali (1993) suggested that adoption and diffusion studies needed to be linked for better understanding of diffusion patterns. McWilliams and Zilberman (1996) attempted to fill the gap by bridging the insights from an adoption and a diffusion model for a non-divisible innovation (computer). McWilliams and Zilberman (1996) conducted their research in two steps: in the first step they test the effect of firm size and education on the time length of computer adoption; in the second step they used the estimation in the first step as an instrument to derive an industry diffusion path.

While diffusion studies are typically ex-post in nature, their approach predicted ex-ante, the diffusion path when only 26 percent of the sample had adopted. Learning by doing was not possible to quantify and test in the first step. However, in the second step, the farmer's education as well as the interaction between the farmer's time of use (estimated from the first step) and education was shown to influence the number of computer applications a farmer uses—serving as a proxy for the farmers' intensity of technology use. Since logit and probit evaluate the probability of a firm having adopted an innovation or new technology by a given time, the empirical models relying on logit and probit did not explicitly address the effect of variables on the speed of adoption. Tobit analysis was shown to provide superior results to the traditional logit and probit analysis due to the increased information provided by the time of adoption data since tobit took into account the heterogeneity of adoption time among those who had adopted. By forecasting who would adopt and when, the authors derived a diffusion that was theoretically motivated by the underlying adoption structure and analysis.

Spatial diffusion

Another key limitation of aggregate models of innovation diffusion is that they are exclusively temporal in nature and have largely ignored the spatial neighborhood effect in the diffusion process.

Indeed, Marra, Hubbell, and Carlson (2001), Ellison and Fudenberg (1993) and other adoption studies have pointed to the relevance of various mechanisms of learning, including the neighborhood effect. If a new technology is "popular" within the decision makers' "window" of relevant potential adopters, then they are more likely to adopt it.

Empirically, neighborhood effects on adoption have been found to be significant (Gardner, 1989; Thrall, 1988). Diffusion models should be able to account and test for such effects.

A parallel concept of learning gives rise to "*spatial diffusion*" models which focus on the effects of space as a major influence (Onsrud, 1991). In the area of spatial diffusion, the pioneer work belongs to Hägerstrand (1967, 1981). He initially developed a mathematical model to describe how an innovation should be expected to diffuse over space and time. Within the context of this model, he determined that the probability of contact was a negative function of distance[4] and he derived various patterns of innovation through simulation and other empirical analysis. His model has been utilized and modified to suit various innovations (e.g. Baptista, 1999).

Hägerstrand's classical diffusion model took into account time and space and as well as the contact between early adopters and the susceptible population. His model divided time and space into discrete periods such as years and cell, respectively. The Mean Information Field (MIF) was created to describe the probability of contact at different distances and directions. Since the MIF involved spatial proximity, physical barriers such as lake and mountains affected MIF. The potential adopters are assumed to receive a number of contacts before adoption took place. The process was repeated and continued for several periods so that areas with larger numbers of possible adopters tended to have more adopters and contactors. Details of how to create MIF can be found in Morrill (1988, p. 26-29).

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[4] The proxy of spatial proximity of this dissertation utilizes this concept where the further the sources of information from the adoption location, the less probability of contact, then the less information transmission to the potential adopters' location.

Mahajan and Peterson (1985) paralleled Hägerstrand's view of diffusion as the information disseminated through mass media and interpersonal contact. Three empirical regularities associated with Hägerstrand's findings were an S-shaped curve, a hierarchical effect (larger center would expect to be diffused prior to smaller center), and a neighborhood effect (wavelike fashion outward from an urban center to neighborhood rather than remote area). In adoption studies, the neighborhood effect is similar to learning from others. Neighborhood effect in adoption studies is mainly used just for an explanatory variable to reflect learning process—not necessarily reflected as the wavelike phenomena discovered by Hägerstrand. Diffusion models in marketing and other empirical research have generally focused on predicting the cumulative number of adopters, and examined the influence of the firm size, imitation effects, and communication via alternative channels (mass media and interpersonal communications). Interpersonal communication including non-verbal observations, has been found to be an important predictor of the speed and shape of the S-shaped pattern of the diffusion process in social systems (Mahajan et al., 2000).

Morrill (1988) concluded two key elements of spatial diffusion were phenomenon and spread. Phenomenon can be material (human settlement) or immaterial (idea or behavior), and must have a real place of origin. Examples of material phenomena were High Yield Varieties seed, while examples of immaterial phenomena were religious believe. Phenomenon must be transferable. Agents can be inanimate (wind, water, and highway) or animate (animals and people).

Morrill suggested that the nature of "spread" or movement from an "origin" implied a spatial continuity. The idea of spatial continuity, in turn, was captured in the statistical concept of spatial autocorrelation, which implies that what happens at one place is in part a function of what has already happened at nearby places.

Empirical applications of spatial diffusion models for agricultural innovations are indeed very few. Zhang *et al*. (2002) investigated factors influencing rate of diffusion of high-yielding varieties (HYVs). A panel data set covering 25 years, starting in 1970, for 280 districts in rural India was used. Their study demonstrated that early successful adopters tend to have a larger neighborhood effect than early unsuccessful adopters.

In the Zhang et al. study, the decision variable was the percentage of total planted area with HYVs of rice, wheat, and maize taking values between 0 and 1. Zhang et al. assumed that farmers grew only one crop on a unit of land and there were two technologies available for farmers: traditional varieties and superior, but riskier, HYVs.

A Tobit model was used to explain the diffusion pattern of HYVs. In order to empirically calculate appropriate neighboring factors, they tested four different specifications of the weight of neighboring proxies. They employed geographic information systems (GIS) to calculate different proxy indicators of the neighborhood effects. The first proxy used the average shares of HYV adoption among neighboring region, a common practice in other similar studies. A second proxy assigned nonzero equal weight to the regions where higher yields were present and zero to the regions where the lower yields existed. A third assigned a weight to the highest yield among neighboring regions, and zero to the rest of the neighboring regions. In addition to neighboring effects, lagged dependent variables representing dynamic learning effects, human capital, and physical infrastructure were also included in the Tobit model. They used logarithm of literacy level (education) as a proxy for human capital, the portion of irrigated area and the road density (total length divided by the total geographic area) as the proxies of physical infrastructure.

Results confirmed their hypotheses that early successful adoptions were positively statistically significant. Education and irrigation also played positive and significant roles. They also compared empirical models with and without lagged dependent variables. The findings showed that models with lagged dependent variable served as a short-run relationship, whereas a model without lagged dependent variable represented a long-run relationship. Interestingly, a model without lagged dependent variable had much higher coefficient estimates in other independent variables, particularly in neighboring effect. Furthermore, the road density, which was not significant in model with lagged dependent variable, turned to be statistically significant in the model without lagged dependent variable. It was then concluded that infrastructure had significant impacts on the long-run diffusion model.

Implications for Modeling

Risk, uncertainty and learning play a number of distinct roles in the process of adopting a new technology. Sunk costs (irreversibility of the investment), operational costs, and uncertain returns largely vary according to types of new technology. Typically, divisible innovation allows farmers to proportionally adopt without large sunk costs and is irreversible. Many agricultural innovations were available to farmers as a bundle (fertilizer, pesticide, and high yield varieties), and can be adopted as a whole or in sequential fashion. However, some agricultural innovation such as new irrigation systems may be associated with considerable sunk costs, making it difficult to revert back to the former technology. Risk also varies proportionally according to the investment and irreversibility.

Previous studies on the economics of technology adoption under uncertainty have taken at least two paths: (1) investment in a durable asset with an uncertain payoff, and (2) relationship between the riskiness of the technology and the utility of a risk-averse decision maker. Net present value approaches and option value approaches are used to estimate future returns of a new technology. The option value approach can be used to incorporate the delay to adopt in order to observe earlier adopters' experience with the technology. Due to the difficulties to observe and measure risk and uncertainties, very few previous empirical studies were able to use direct interview techniques to investigate the effect of farmers' risk attitude and perception of riskiness on their decisions.

Learning is the mechanism of potential adopters in updating their information and knowledge toward the existence (awareness) of the technology, the ability to implement (skill development), and outcomes of new technology along with its costs and benefits. Accordingly, updated information through time reduces the risk associated with new innovation. Potential adopters can obtain information from various channels, depending upon the directions of information flow: active information—potential adopters seek for information[5], or passive information—information finds potential adopters without fees.

Typically, learning mechanisms consist of learning by doing, learning from others, and learning from external sources. Experience is accumulated through learning

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[5] Experience (self-learning or learning by doing) can be considered a subset of active information, and in this case, active information incurs extra costs (or investments). Costs can be derived from investing in the new technology as learning by doing process or purchasing information. Unlike self-learning, imitation is active information without extra costs, and derived from learning from others or neighborhood effects (Ellison and Fudenberg 1993.)

by doing. Learning from others typically involves neighbors who are located nearby and share similar characteristics. External sources of learning include university extension and other information brokers such as marketing agents and media sources.

Potential adopters can gain knowledge on new technologies directly from the same exact technologies used by others or indirectly from the use of similar technologies. With many sources and large amounts of information, the quality of information becomes critical to the adoption decision. The quality of information received by potential adopters varies with the sources of information, the stage of diffusion process when the information was shared, prior information of users, and the current adoption levels of users. In addition, optimal learning from neighbors usually occurs when it is received from successful early adopters rather than unsuccessful ones.

Innovations can be adopted individually, sequentially, or as a bundle. Through time, potential adopters may find innovation useful and decide to continue or increase adoption rates; on the other hand, adopters may not find innovation beneficial and decide to discontinue its use and dis-adopt.

To summarize, technological adoption and diffusion theories and methods are revisited in this study in the context of adoption and diffusion of US cotton biotechnologies. Learning by doing and learning from others are considered significant influences of adoption among US cotton farmers.

The population of the potential adopters is not considered homogeneous. Farms are assumed to differ in their characteristics (e.g. size, agronomic practices, and use of other technologies like irrigation). Farm location can also point to other significant differences among farms that can influence their behavior towards innovation (e.g.

differential pest pressures). Farm heterogeneity is assumed to explain, in part, differential adoption and diffusion levels in cotton biotechnologies.

US cotton farmers are assumed to form expectations about the potential gains from biotech cotton technologies and any synergies with other agronomic practices (e.g. minimum tillage practices). Perceived gains are considered significant influences of adoption among US cotton farmers.

The significance of such factors in explaining observed adoption levels of a representative sample of farmers and the population of adopters over several years is explicitly tested.

CHAPTER 3

THEORETICAL FRAMEWORK

In this chapter, I develop a theoretical model that examines the adoption decision of a U.S. cotton farmer in the presence of multiple new biotechnology varieties and a traditional one. For this, I extend an optimal control model of technology adoption developed by Kalaitzandonakes and Boggess, 1993 (KB model). The KB model took into account the dynamic process of active and passive learning[6], and adjustment costs in a competitive market. The KB model analyzed two divisible technologies (a traditional and a new technology) and allowed for partial adoption. Specifically, it assumed that the firm allocates a quasi fixed factor[7] (land) between the traditional and the new technology. The profitability of the new technology is considered uncertain. The theoretical model developed here expands the KB model to incorporate multiple new technologies that compete with a traditional technology for the quasi fixed factor. It also allows for cross-learning. The firm is assumed to solve a two-step optimization problem.

1st step:

The Firm allocates the quasi fixed factor Z among

- A traditional divisible technology (A) (z_1)
- A new divisible technology (B) (z_2)
- A new divisible technology (C) (z_3)

[6] Accumulation of information and learning are often incorporated to allow the firms to update their perceptions on the profitability and/or the riskiness of the new technology over time.
[7] Factors of production that are in a fixed amount, independent of the output of the firm, in the short run.

2nd step:

The Firm determines the variable input mix conditionally on the allocation of the quasi fixed factor *Z*. In other words, the firm decides the variable input mix by maximizing short run profits.

$$\pi_1 = \pi_1(p, w, z_1)$$

$$\pi_2 = \pi_2(p, w, z_2) + g_2(p, w, z_2)e_2$$

$$\pi_3 = \pi_3(p, w, z_3) + g_3(p, w, z_3)e_3$$

Where *p* & *w* are the output and input prices, respectively. *P* and *w* are considered exogenous to the firm. The traditional technology is assumed deterministic[8] whereas the new technologies are assumed stochastic. However, the perception of riskiness diminishes over time, so *g* is assumed concave in *z* with *g(0)=0* and *e~N(0,v)* denoting uncertainties in returns.

The total available land is *z* and can be allocated to any of these technologies, individually or in combination.

$$z = z_1 + z_2 + z_3$$

For a given set of *p* and *w,* profits can be expressed as[9]:

$$\pi = \pi_1(z - z_2 - z_3) + \pi_2(z_2) + g_2(z_2)e_2 + \pi_3(z_3) + g_3(z_3)e_3$$

Thus, I assume that innovation rents are normally distributed with

Mean: $\overline{\pi} = \pi_1(z - z_2 - z_3) + \pi_2(z_2) + \pi_3(z_3)$

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[8] Presumably farmers have been planted traditional varieties for a numbers of years and assumed to be able to estimate their profit using traditional cotton seeds.

[9] To set up the problem with more than one new technology, all new technologies can be rewritten as:

$$\pi_i = \sum_{i=2}^{n} \pi_i(p, w, z_i) + g_i(p, w, z_i)e_i$$

Variance: $v_x = g_2{}^2(z_2)v_2 + g_3{}^2(z_3)v_3$

Also, I assume that the risk preferences of the firm can be adequately represented by a negative exponential utility function:

$U(\pi) = -\exp(\theta\pi)$

In this way, the optimal allocation of the fixed factor between the three alternative technologies could be determined within the typical Arrow-Pratt Mean-Variance framework. The Maximum Expected Utility within a single period then is given by:

$$Max \quad R = \bar{\pi} - \frac{\theta}{2}v_x$$

or

$$Max \;\; R = \pi_1(z - z_2 - z_3) + \pi_2(z_2) + \pi_3(z_3) - \frac{\theta}{2}g_2{}^2(z_2)v_2 - \frac{\theta}{2}g_3{}^2(z_3)v_3$$

where θ is the Arrow-Pratt risk aversion coefficient. Hence, the levels of z_2 and z_3 that maximize *R* will also maximize $U(\pi)$.

There are at least three reasons that the firm might extend the adoption of a divisible innovation over several periods, including short run capital availability constraints, adjustment costs, and learning.

The firm is assumed to maximize the present value of a stream of expected utilities by choosing the temporal path of $Z_2(t)$ and $Z_3(t)$ subject to the fixed factor availability constraint.

Assumptions:

- The stock of knowledge with respect to the profit of a new technology increases with rate of adoption through learning.

- As the stock of knowledge increases, the perceived riskiness in the return of a new technology decreases over time through
    - Learning by doing (experience) and investment.
        - Farmers can invest in technology *B* today and expect to gain experience on its profitability through learning by doing in the following periods.
        - Farmers can also invest in similar technology *C* today and expect to gain some experience on the profitability of B (though less than if they invested in A directly); hence learning through similar technologies is assumed.
    - Passive learning (from external sources & imitation from others & neighbors) without investment
        - Farmers expect to gain more information regarding the new technologies as time goes by.
- Adoption process entails costs of adjustment

Based on the above assumptions, the producer's adoption problem can be formally stated as

$$\underset{z_2, z_3}{Max} \int_0^T e^{-rt} \begin{bmatrix} \pi_1(z - z_2(t) - z_3(t)) + \pi_2(z_2(t)) + \pi_3(z_3(t)) \\ -\frac{\theta}{2} g_2{}^2(z_2(t))v_2(t) - \frac{\theta}{2} g_3{}^2(z_3(t))v_3(t) \\ -C_2\left(z_2(t), \dot{z}_2(t)\right) - C_3\left(z_3(t), \dot{z}_3(t)\right) \end{bmatrix} dt$$

Subject to

$\dot{v}_2(t) = f\left(z_2(t), \dot{z}_2(t), \dot{z}_3(t), t \right)$ [temporal change in perceived riskiness of new technology (*B*)]

$\dot{v}_3(t) = f\left(z_3(t), \dot{z}_3(t), \dot{z}_2(t), t \right)$ [temporal change in perceived riskiness of new technology (*C*)]

$v_2(0) = v_3(0) = v_0$ at the beginning period *t=0*, risks associated with technology *B&*C are assumed equal to v_0

$z_2(0) = z_3(0) = 0$ at the beginning *t=0*, none of the quasi fixed factor (land) is allocated to either new technology

$0 \leq z_2 \leq z$ adjustment costs are incurred only for a positive adoption of z_2

$0 \leq z_3 \leq z$ adjustment costs are incurred only for a positive adoption of z_3

Where:

- e^{-rt} denotes that future periods are discounted at rate *r*
- $Z_2(t)$ & $Z_3(t)$ are the stocks of technologies *B&C,* respectively, at time *t*
- $\dot{Z}_2(t)$ & $\dot{Z}_3(t)$ denote the rates of adoption for *B&C,* respectively
- *t* is incorporated into the equation of motion to imply that additional information becomes available from external sources to users through passive learning (learning from others). The longer the period, the more information is available to the firm.
- *C(•)* denotes the disutility resulting from costs of adjustment and is assumed to be increasing at an increasing rate in $\dot{z}$ and a decreasing rate in *z.*

In order to test whether the assumed learning mechanisms influence the rate or speed of adoption, specific functional forms of π_1, π_2, π_3, g_2, g_3, f, C_2, C_3 much like those assumed in the KB model:

π_1, π_2, π_3 are assumed quadratic and weakly separable in *z*.

$g_2 = \left(\delta \cdot z_2(t)\right)^{\frac{1}{2}}$ implies that the uncertainty associated with the innovation rent of technology *B* is increasing at a decreasing rate,

$g_3 = \left(\delta \cdot z_3(t)\right)^{\frac{1}{2}}$ implies that the uncertainty associated with the innovation rent of technology *C* is increasing at a decreasing rate,

$C_2 = \frac{k}{2} \dot{z}_2^{\,2}(t)$ the adjustment cost of technology *B* is proportional to Stoneman's adjustment cost, and

$C_3 = \frac{k}{2} \dot{z}_3^{\,2}(t)$ the adjustment cost of technology *C* is proportional to Stoneman's adjustment cost.

Hence, it is assumed that the rate of change in the variance of the innovation rents decreases proportionally as the rate of adoption increases. Given these assumptions and suppressing the time argument for simplicity, the problem may be stated in calculus of variation as

$$\underset{z_2,z_3}{Max}\int_0^T e^{-rt}\begin{bmatrix} \alpha_0+\alpha_1(z-z_2-z_3)+\alpha_2(z-z_2-z_3)^2 \\ +\beta_0+\beta_1(z_2)+\beta_2(z_2)^2 \\ +\gamma_0+\gamma_1(z_3)+\gamma_2(z_3)^2 \\ -\frac{\theta}{2}\delta\cdot z_2\cdot v_2-\frac{\theta}{2}\delta\cdot z_3\cdot v_3 \\ -\frac{k}{2}\dot{z}_2^{\,2}-\frac{k}{2}\dot{z}_3^{\,2} \end{bmatrix}dt$$

Subject to:

$$\dot{v}_2=\eta_2\,\dot{z}_2+\eta_4\,\dot{z}_3$$

$$\dot{v}_3=\eta_3\,\dot{z}_3+\eta_5\,\dot{z}_2$$

$$v_2(0)=v_3(0)=v_0$$

$$z_2(0)=z_3(0)=0$$

$$0\le z_2\le z$$

$$0\le z_3\le z$$

With $\alpha_1>0,\alpha_2<0,\beta_1>0,\beta_2<0,\gamma_1>0,\gamma_2<0,\theta>0,\delta>0$, $\eta_2<0$, $\eta_3<0$, $\eta_4<0$, $\eta_5<0$, $\frac{\eta_2}{\eta_4}>1$ and $\frac{\eta_3}{\eta_5}>1$ (the last two assumptions emphasize that more weight is placed on learning by doing through the use of the exact technology than through use of a similar technology).

The solution of the above problem can be derived within the framework of calculus of variation or of optimal control. In either case, the resulting optimal adoption paths ($z_2^*(t)$, $z_3^*(t)$) should be the same.

The problem is converted into a standard optimal control form by defining $u_2(t) = \dot{z}_2(t)$ and $u_3(t) = \dot{z}_3(t)$. The $u_2(t)$ and $u_3(t)$ are considered the control (instruments) and $z_2(t)$, $z_3(t)$, $v_2(t)$, and $v_3(t)$ the state variables. Hence, the firm's optimization probably becomes:

$$\underset{z_2, z_3}{Max} \int_0^T e^{-rt} \begin{bmatrix} \alpha_{00} + \alpha_{11} z_2 + \alpha_{22} z_3 + 2\alpha_2 z_2 z_3 + \alpha_2 z_2^2 + \alpha_2 z_3^2 \\ + \beta_0 + \beta_1 (z_2) + \beta_2 (z_2)^2 \\ + \gamma_0 + \gamma_1 (z_3) + \gamma_2 (z_3)^2 \\ -\frac{\theta}{2} \delta \cdot z_2 \cdot v_2 - \frac{\theta}{2} \delta \cdot z_3 \cdot v_3 \\ -\frac{k}{2} u_2{}^2 - \frac{k}{2} u_3{}^2 \end{bmatrix} dt$$

Where:

$$\alpha_{00} = \alpha_0 + \alpha_1 z + \alpha_2 z^2$$

$$\alpha_{11} = \alpha_{22} = -\alpha_1 - 2\alpha_2 z$$

Subject to

$$\dot{z}_2 = u_2$$

$$\dot{z}_3 = u_3$$

$$\dot{v}_2 = \eta_2 u_2 + \eta_4 u_3$$

$$\dot{v}_3 = \eta_3 u_3 + \eta_5 u_2$$

$$v_2(0) = v_3(0) = v_0$$

$$z_2(0) = z_3(0) = 0$$

$0 \le z_2 \le z$

$0 \le z_3 \le z$

The (discounted) Hamiltonian is then given by

$$H(\cdot) = e^{-rt} \begin{bmatrix} \alpha_{00} + \alpha_{11} z_2 + \alpha_{22} z_3 + 2\alpha_2 z_2 z_3 + \alpha_2 z_2^2 + \alpha_2 z_3^2 \\ + \beta_0 + \beta_1 (z_2) + \beta_2 (z_2)^2 \\ + \gamma_0 + \gamma_1 (z_3) + \gamma_2 (z_3)^2 \\ - \frac{\theta}{2} \delta \cdot z_2 \cdot v_2 - \frac{\theta}{2} \delta \cdot z_3 \cdot v_3 \\ - \frac{k}{2} u_2{}^2 - \frac{k}{2} u_3{}^2 \end{bmatrix} + \begin{bmatrix} + \lambda_2 u_2 + \lambda_3 u_3 \\ + \lambda_4 (\eta_2 u_2 + \eta_4 u_3) \\ + \lambda_5 (\eta_3 u_3 + \eta_5 u_2) \end{bmatrix}$$

From the discounted Hamiltonian to the current Hamiltonian, I define the current value multiplier $\mu(t)$ as:

$$\mu_i(t) = e^{rt} \lambda_i(t) \Leftrightarrow \lambda_i(t) = e^{-rt} \mu_i(t),$$

And, through it, the <u>current</u> value Hamiltonian is

$$H^c(\cdot) = \begin{bmatrix} \alpha_{00} + \alpha_{11} z_2 + \alpha_{22} z_3 + 2\alpha_2 z_2 z_3 + \alpha_2 z_2^2 + \alpha_2 z_3^2 \\ + \beta_0 + \beta_1 (z_2) + \beta_2 (z_2)^2 \\ + \gamma_0 + \gamma_1 (z_3) + \gamma_2 (z_3)^2 \\ - \frac{\theta}{2} \delta \cdot z_2 \cdot v_2 - \frac{\theta}{2} \delta \cdot z_3 \cdot v_3 \\ - \frac{k}{2} u_2{}^2 - \frac{k}{2} u_3{}^2 \\ + \mu_2 u_2 + \mu_3 u_3 \\ + \mu_4 \eta_2 u_2 + \mu_4 \eta_4 u_3 \\ + \mu_5 \eta_3 u_3 + \mu_5 \eta_5 u_2 \end{bmatrix}$$

Applying the Maximum Principle I obtain

$$\frac{\partial H}{\partial \lambda_i} = \frac{\partial H^c}{\partial \mu_i} = \dot{z}_i(t)(i = 2,3)$$

$$\frac{\partial H}{\partial \lambda_2} = \frac{\partial H^c}{\partial \mu_2} = \dot{z}_2 = u_2 \tag{H.1}$$

$$\frac{\partial H}{\partial \lambda_3} = \frac{\partial H^c}{\partial \mu_3} = \dot{z}_3 = u_3 \tag{H.2}$$

$$\frac{\partial H}{\partial \lambda_4} = \frac{\partial H^c}{\partial \mu_4} = \dot{v}_2(t) = \eta_2 u_2 + \eta_4 u_3 \tag{H.3}$$

$$\frac{\partial H}{\partial \lambda_5} = \frac{\partial H^c}{\partial \mu_5} = \dot{v}_3(t) = \eta_3 u_3 + \eta_5 u_2 \tag{H.4}$$

And the conditions of the control variables are:

$$\frac{\partial H}{\partial u_2} = 0 \iff \frac{\partial H^c}{\partial u_2} = -ku_2 + \mu_2 + \mu_4\eta_2 + \mu_5\eta_5 = 0 \tag{H.5}$$

$$\frac{\partial H}{\partial u_3} = 0 \iff \frac{\partial H^c}{\partial u_3} = -ku_3 + \mu_3 + \mu_5\eta_3 + \mu_4\eta_4 = 0 \tag{H.6}$$

Then the conditions of the states are:

$$\frac{\partial H}{\partial z_2} = -\dot{\lambda}_2(t) \Leftrightarrow \frac{\partial H^c}{\partial z_2} = r\mu_2(t) - \dot{\mu}_2(t) = \alpha_{111} + \alpha_{222}z_2 + \alpha_{333}z_3 - \theta_1 v_2$$

Thus, $$-\frac{\partial H^c}{\partial z_2} = -\alpha_{111} - \alpha_{222}z_2 - \alpha_{333}z_3 + \theta_1 v_2 = \dot{\mu}_2(t) - r\mu_2(t) \tag{H.7}$$

$$\frac{\partial H}{\partial z_3} = -\dot{\lambda}_3(t) \Leftrightarrow \frac{\partial H^c}{\partial z_3} = r\mu_3(t) - \dot{\mu}_3(t) = \alpha_{444} + \alpha_{555}z_2 + \alpha_{666}z_3 - \theta_2 v_3$$

Thus, $$-\frac{\partial H^c}{\partial z_3} = -\alpha_{444} - \alpha_{555}z_2 - \alpha_{666}z_3 + \theta_2 v_3 = \dot{\mu}_3(t) - r\mu_3(t) \tag{H.8}$$

$$\frac{\partial H}{\partial v_2} = -\dot{\lambda}_4(t) \Leftrightarrow \frac{\partial H^c}{\partial v_2} = r\mu_4(t) - \dot{\mu}_4(t) = -\frac{\theta}{2}\delta \cdot z_2$$

Thus, $$-\frac{\partial H^c}{\partial v_2} = \theta_1 z_2 = \dot{\mu}_4(t) - r\mu_4(t) \tag{H.9}$$

$$\frac{\partial H}{\partial v_3} = -\dot{\lambda}_5(t) \Leftrightarrow \frac{\partial H^c}{\partial v_3} = r\mu_5(t) - \dot{\mu}_5(t) = -\frac{\theta}{2}\delta \cdot z_3$$

Thus, $-\frac{\partial H^c}{\partial v_3} = \theta_2 z_3 = \dot{\mu}_5(t) - r\mu_5(t)$ (H.10)

where:

$\alpha_{111} = \alpha_{11} + \beta_1$

$\alpha_{222} = 2\alpha_2 + 2\beta_2 = 2(\alpha_2 + \beta_2)$

$\alpha_{333} = \alpha_{555} = 2\alpha_2$

$\alpha_{444} = \alpha_{22} + \gamma_1$

$\alpha_{555} = \alpha_{333} = 2\alpha_2$

$\alpha_{666} = 2\alpha_2 + 2\gamma_2 = 2(\alpha_2 + \gamma_2)$

$\theta_1 = \theta_2 = \frac{\theta}{2}\delta$

By convention, α_{111} and α_{444} are assumed to be positive and α_{222}, α_{333}, α_{555}, and α_{666} are assumed negative. These assumptions imply that a transfer of one unit of the quasi-fixed factor *z* from the old technology to either new technology results in increasing profits at a decreasing rate.

From (H.1) and (H.2) with (H.3), it is implied that $\eta_2 \dot{z}_2 + \eta_4 \dot{z}_3 = \dot{v}_2$. Similarly, from (H.1) and (H.2) with (H.4), it is implied that $\eta_3 \dot{z}_3 + \eta_5 \dot{z}_2 = \dot{v}_3$, then

$$\dot{v}_2 = \eta_2 \dot{z}_2 + \eta_4 \dot{z}_3 \Rightarrow \dot{v}_2(t) = \eta_2 \dot{z}_2(t) + \eta_4 \dot{z}_3(t)$$

$$\int \frac{dv_2}{dt} dt = \eta_2 \int \frac{dz_2}{dt} dt + \eta_4 \int \frac{dz_3}{dt} dt$$

$v_2 = \eta_2 z_2 + \eta_4 z_3 + C \Rightarrow v_2(t) = \eta_2 z_2(t) + \eta_4 z_3(t) + C$

Now:

Let *t=0*, $v_2(0) = \eta_2 z_2(0) + \eta_4 z_3(0) + C$;

Then, $v_2(0) = C$; [since $z_2(0) = z_3(0) = 0$]& [$v_2(0) = v_0$] from the boundary conditions

Thus, $v_2 = \eta_2 z_2 + \eta_4 z_3 + v_0$ (H.11)

Similarly, $v_3 = \eta_3 z_3 + \eta_5 z_2 + v_0$ (H.12)

A linear system of first-order differential equations is derived as

$$\dot{z}_2 = \frac{1}{k}\mu_2 + \frac{\eta_2}{k}\mu_4 + \frac{\eta_5}{k}\mu_5 = 0 \quad \text{(D.E.1)}$$

By substituting (H.1) into (H.5)

$$\dot{z}_3 = \frac{1}{k}\mu_3 + \frac{\eta_4}{k}\mu_4 + \frac{\eta_3}{k}\mu_5 = 0 \quad \text{(D.E.2)}$$

By substituting (H.2) into (H.6)

$$\dot{\mu}_2 - r\mu_2 - \vartheta_2 z_2 - \vartheta_6 z_3 = \vartheta_1 \quad \text{(D.E.3)}$$

(with $\vartheta_2 = -\alpha_{222} + \theta_1\eta_2$; $\vartheta_6 = -\alpha_{333} + \theta_1\eta_4$ and $\vartheta_1 = -\alpha_{111} + \theta_1 v_0$) from substituting (H.7) into (H.11)

$$\dot{\mu}_3 - r\mu_3 - \vartheta_7 z_2 - \vartheta_4 z_3 = \vartheta_3 \quad \text{(D.E.4)}$$

(with $\vartheta_4 = -\alpha_{666} + \theta_2\eta_3$; $\vartheta_7 = -\alpha_{555} + \theta_2\eta_5$ and $\vartheta_3 = -\alpha_{444} + \theta_2 v_0$) from substituting (H.8) into (H.12)

Then, rearranging (H.9)&(H.10), gives

$$\dot{\mu}_4(t) - r\mu_4(t) - \theta_1 z_2 = 0 \quad \text{(D.E.5)}$$

$$\dot{\mu}_5(t) - r\mu_5(t) - \theta_2 z_3 = 0 \quad \text{(D.E.6)}$$

To solve for $\overset{*}{z}_2(t)$ and $\overset{*}{z}_3(t)$, the solutions of $\overset{*}{\mu}_2(t)$, $\overset{*}{\mu}_3(t)$, $\overset{*}{\mu}_4(t)$, and $\overset{*}{\mu}_5(t)$ need to be solved as a system of equations. Most systems of linear ordinary differential equations deal with two variables, which can be solved by a 2X2 matrix that utilizes the trace and determinant of matrix to derive real and distinct roots. However, once the matrix is of larger dimension, this step becomes complex.

To attempt to solve this 6X6 matrix, some assumptions need to be made. Obviously, the 6 differential equations are non-homogenous.[10] Instead of solving for the

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[10] Differential equations (D.E.) are non-homogeneous. Briefly, the solution of a non-homogeneous individual linear differential equation $\frac{dy}{dt} + ay = b$ will consist of two terms: the complementary integral (y_c) and the particular integral (y_p). The complementary function (y_c) is the general solution of the reduced equation, which is the general solution in the homogenous case. The particular integral (y_p) is simply any particular solution of the complete equation.

The y_c is the general solution of the reduced equation in the homogenous case (when $b=0$), and it can be derived as:

$$\frac{dy}{dt} + ay = 0 \Rightarrow \frac{1}{y}\frac{dy}{dt} = -a \Rightarrow \frac{1}{y}dy = -a \cdot dt$$

$$\int \frac{1}{y}dy = \int -a \cdot dt \Rightarrow \ln y + c_1 = -at + c_2 \Rightarrow e^{\ln y} \cdot e^{c_1} = e^{-at} \cdot e^{c_2}$$

The general solution of homogeneous case is $y_c = y(t) = A \cdot e^{-at}$ where $A = \frac{e^{c_2}}{e^{c_1}} = e^{c_2 - c_1}$

The definite solution of homogeneous case is $y_c = y(t) = y(0) \cdot e^{-at}$

The y_p can be anything including the simplest possible type of solution, the constant *(y=k)*. According to $\frac{dy}{dt} + ay = b$, if $y=k$, $\frac{dy}{dt} = 0$, then $ay = b$ and $y = \frac{b}{a}$ as long as $a \neq 0$. Thus, $y_p = \frac{b}{a}$ ($a \neq 0$)

Finally,

$$\overset{*}{y}(t) = y_c + y_p$$

$$y_c = A \cdot e^{-at}$$

complete solution (for both homogenous and particular integral terms), reduced solutions (for homogenous as complementary function only) can be sought instead. Of interest is to examine the direction of the influence of learning from exact and similar technologies on the rate of adoption of the new technologies. To do so, the real and distinct root needs to be determined upon deriving the homogenous solutions of the non-homogenous system of differential equations.[11]

To solve for a system of six differential equations, the system is rearranged and follows:

$$\dot{z}_2 = \frac{1}{k}\mu_2 + \frac{\eta_2}{k}\mu_4 + \frac{\eta_5}{k}\mu_5 = 0 \qquad \text{(D.E.1)}$$

$$\dot{z}_3 = \frac{1}{k}\mu_3 + \frac{\eta_4}{k}\mu_4 + \frac{\eta_3}{k}\mu_5 = 0 \qquad \text{(D.E.2)}$$

$$\dot{\mu}_2 - r\mu_2 - \vartheta_2 z_2 - \vartheta_6 z_3 = \vartheta_1 \qquad \text{(D.E.3)}$$

(with $\vartheta_2 = -\alpha_{222} + \theta_1\eta_2$; $\vartheta_6 = -\alpha_{333} + \theta_1\eta_4$ and $\vartheta_1 = -\alpha_{111} + \theta_1 v_0$)

$$\dot{\mu}_3 - r\mu_3 - \vartheta_7 z_2 - \vartheta_4 z_3 = \vartheta_3 \qquad \text{(D.E.4)}$$

(with $\vartheta_4 = -\alpha_{666} + \theta_2\eta_3$; $\vartheta_7 = -\alpha_{555} + \theta_2\eta_5$ and $\vartheta_3 = -\alpha_{444} + \theta_2 v_0$)

$$\dot{\mu}_4(t) - r\mu_4(t) - \theta_1 z_2 = 0 \qquad \text{(D.E.5)}$$

$$\dot{\mu}_5(t) - r\mu_5(t) - \theta_2 z_3 = 0 \qquad \text{(D.E.6)}$$

$y_p = \frac{b}{a}$ $(a \neq 0)$

[11] Further research can focus on solving the complete equation since the equilibrium level of adoption requires particular integral term to be solved. Once the real and distinct root is determined, it provides the direction of the marginal increase in the farmer's learning on optimal level of adoption. In addition to learning the impacts of cost adjustment and risk aversion con adoption can also be determined.

To find a non-zero column vector **v** and scalar **λ** (which may be 0) such that ***A*v= λv (**a column vector **v** is called eigenvector of ***A***, and the scalar **λ** is called eigenvalue of ***A*** for **v**), all the eigenvector and eigenvalues of the following square matrix *A* need to be found:

$$\begin{bmatrix} 0 & 0 & \frac{1}{k} & 0 & \frac{\eta_2}{k} & \frac{\eta_5}{k} \\ 0 & 0 & 0 & \frac{1}{k} & \frac{\eta_4}{k} & \frac{\eta_3}{k} \\ \vartheta_2 & \vartheta_6 & r & 0 & 0 & 0 \\ \vartheta_7 & \vartheta_4 & 0 & r & 0 & 0 \\ \theta_1 & 0 & 0 & 0 & r & 0 \\ 0 & \theta_2 & 0 & 0 & 0 & r \end{bmatrix}$$

A system of first order linear ordinary differential equation can then be expressed as

$$\begin{bmatrix} \dot{z}_2 \\ \dot{z}_3 \\ \dot{\mu}_2 \\ \dot{\mu}_3 \\ \dot{\mu}_4 \\ \dot{\mu}_5 \end{bmatrix} = \begin{bmatrix} 0 & 0 & \frac{1}{k} & 0 & \frac{\eta_2}{k} & \frac{\eta_5}{k} \\ 0 & 0 & 0 & \frac{1}{k} & \frac{\eta_4}{k} & \frac{\eta_3}{k} \\ \vartheta_2 & \vartheta_6 & r & 0 & 0 & 0 \\ \vartheta_7 & \vartheta_4 & 0 & r & 0 & 0 \\ \theta_1 & 0 & 0 & 0 & r & 0 \\ 0 & \theta_2 & 0 & 0 & 0 & r \end{bmatrix} \begin{bmatrix} z_2 \\ z_3 \\ \mu_2 \\ \mu_3 \\ \mu_4 \\ \mu_5 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \vartheta_1 \\ \vartheta_3 \\ 0 \\ 0 \end{bmatrix}$$

=

or in the matrix form

$$\dot{X} = AX + B$$

where the square matrix A, which is assumed to have an inverse, contains only constants. B is function of *t.* One way to solve the system is to **diagonalize** the coefficient matrix *A* and hence decouple these equations.

Suppose that $\lambda_1, \lambda_2, ..., \lambda_n$ and $v_1, v_2, ..., v_n$ are distinct eigenvalues and associated eigenvectors of

$$AX = \lambda X$$

$$\begin{bmatrix} 0 & 0 & \frac{1}{k} & 0 & \frac{\eta_2}{k} & \frac{\eta_5}{k} \\ 0 & 0 & 0 & \frac{1}{k} & \frac{\eta_4}{k} & \frac{\eta_3}{k} \\ \vartheta_2 & \vartheta_6 & r & 0 & 0 & 0 \\ \vartheta_7 & \vartheta_4 & 0 & r & 0 & 0 \\ \theta_1 & 0 & 0 & 0 & r & 0 \\ 0 & \theta_2 & 0 & 0 & 0 & r \end{bmatrix} \begin{bmatrix} z_2 \\ z_3 \\ \mu_2 \\ \mu_3 \\ \mu_4 \\ \mu_5 \end{bmatrix} = \lambda \begin{bmatrix} z_2 \\ z_3 \\ \mu_2 \\ \mu_3 \\ \mu_4 \\ \mu_5 \end{bmatrix}$$

The augmented matrix for these equations is therefore

$$\left[\begin{array}{cccccc|c} -\lambda & 0 & \frac{1}{k} & 0 & \frac{\eta_2}{k} & \frac{\eta_5}{k} & 0 \\ 0 & -\lambda & 0 & \frac{1}{k} & \frac{\eta_4}{k} & \frac{\eta_3}{k} & 0 \\ \vartheta_2 & \vartheta_6 & r-\lambda & 0 & 0 & 0 & \vartheta_1 \\ \vartheta_7 & \vartheta_4 & 0 & r-\lambda & 0 & 0 & \vartheta_3 \\ \theta_1 & 0 & 0 & 0 & r-\lambda & 0 & 0 \\ 0 & \theta_2 & 0 & 0 & 0 & r-\lambda & 0 \end{array}\right]$$

To process, I assume that all right-hand side values are zero as in the homogenous case[12]. To solve these equations, set the determinant (Det) of this matrix (m), equal to zero so that the optimal λs can be derived. Using *Mathematica,* given $\varphi_2 = \vartheta_2$, $\varphi_4 = \vartheta_4$, $\varphi_6 = \vartheta_6$, $\varphi_7 = \vartheta_7$ [13].

Let's,

$$m = \begin{pmatrix} -\lambda & 0 & 1/k & 0 & \eta_2/k & \eta_5/k \\ 0 & -\lambda & 0 & 1/k & \eta_4/k & \eta_3/k \\ \varphi_2 & \varphi_6 & r-\lambda & 0 & 0 & 0 \\ \varphi_7 & \varphi_4 & 0 & r-\lambda & 0 & 0 \\ \theta_1 & 0 & 0 & 0 & r-\lambda & 0 \\ 0 & \theta_2 & 0 & 0 & 0 & r-\lambda \end{pmatrix}$$

Determinants of m equals

$$\begin{aligned} \text{Det(m)}= \frac{1}{4k^2} \\ &\Big((r-\lambda)^2\big(-8kr\gamma 2\lambda + 4k^2r^2\lambda^2 + 8k\gamma 2\lambda^2 - 8k^2r\lambda^3 + 4k^2\lambda^4 - \\ &\quad 4\gamma 2\delta\theta\eta_2 + 2kr\delta\theta\lambda\eta_2 - 2k\delta\theta\lambda^2\eta_2 + 2kr\delta\theta\lambda\eta_3 - \\ &\quad 2k\delta\theta\lambda^2\eta_3 + \delta^2\theta^2\eta_2\eta_3 - \delta^2\theta^2\eta_4\eta_5 - 8\gamma 2\eta_2\theta_1 + \\ &\quad 4kr\lambda\eta_2\theta_1 - 4k\lambda^2\eta_2\theta_1 + 2\delta\theta\eta_2\eta_3\theta_1 - 2\delta\theta\eta_4^2\theta_1 + \\ &\quad 4kr\lambda\eta_3\theta_2 - 4k\lambda^2\eta_3\theta_2 + 2\delta\theta\eta_2\eta_3\theta_2 - 2\delta\theta\eta_5^2\theta_2 + \\ &\quad 4\eta_2\eta_3\theta_1\theta_2 - 4\eta_4\eta_5\theta_1\theta_2 + \\ &\quad 4\alpha_2\big(4\gamma 2 - 4kr\lambda + 4k\lambda^2 + 4\beta_2 - \delta\theta\eta_3 + \delta\theta\eta_4 + \delta\theta\eta_5 + \\ &\qquad 2\eta_4\theta_1 - \eta_2(\delta\theta + 2\theta_1) - 2\eta_3\theta_2 + 2\eta_5\theta_2\big) + \\ &\quad 4\beta_2(4\gamma 2 + 2k\lambda(-r+\lambda) - \eta_3(\delta\theta + 2\theta_2))\big)\Big) \end{aligned}$$

In order for these equations to have a non-zero solution, set the Det(m) =0[14]. Solving yields eigenvalues and eigenvectors of the matrix. When determinants of m equals to zero, solving for optimal λs yields six optimal λs

[12] Since the right hand side of the augmented matrix is a column of zeros as being assumed in the case of homogenous, row operations cannot change this and so there is no need to write it down.

[13] for notation differences in *Mathematics* software purposes.

[14] This method is equivalent to elementary row (column) operations to reduce the matrix to an echelon form and the echelon form must have a row of zeros.

$$\{\{\lambda_1 \to r\}, \{\lambda_2 \to r\},$$

$$
\begin{aligned}
&\Big\{\lambda_3 \to -\frac{1}{8k^2} \\
&\quad \Big(-4k^2\, r - \sqrt{\Big(16k^4\, r^2 + 16k^2\Big(-4k\,\gamma 2 - 8k\,\alpha_2 - 4k\,\beta_2 + k\,\delta\,\theta\eta_2 +} \\
&\qquad k\,\delta\,\theta\eta_3 + 2k\,\eta_2\,\theta_1 + 2k\,\eta_3\,\theta_2 - \\
&\qquad \frac{1}{2}\sqrt{\big((8k\,\gamma 2 + 16k\,\alpha_2 + 8k\,\beta_2 - 2k\,\delta\,\theta\eta_2 -} \\
&\qquad\quad 2k\,\delta\,\theta\eta_3 - 4k\,\eta_2\,\theta_1 - 4k\,\eta_3\,\theta_2)^2 - \\
&\qquad\quad 16k^2\big(16\gamma 2\,\alpha_2 + 16\gamma 2\,\beta_2 + 16\alpha_2\,\beta_2 - 4\gamma 2\,\delta\,\theta \\
&\qquad\qquad \eta_2 - 4\delta\,\theta\alpha_2\,\eta_2 - 4\delta\,\theta\alpha_2\,\eta_3 - 4\delta\,\theta\,\beta_2\,\eta_3 + \\
&\qquad\qquad \delta^2\theta^2\,\eta_2\,\eta_3 + 4\delta\,\theta\alpha_2\,\eta_4 + 4\delta\,\theta\alpha_2\,\eta_5 - \delta^2\,\theta^2 \\
&\qquad\qquad \eta_4\,\eta_5 - 8\gamma 2\,\eta_2\,\theta_1 - 8\alpha_2\,\eta_2\,\theta_1 + 2\delta\,\theta\eta_2\,\eta_3 \\
&\qquad\qquad \theta_1 + 8\alpha_2\,\eta_4\,\theta_1 - 2\delta\,\theta\eta_4^2\,\theta_1 - 8\alpha_2\,\eta_3\,\theta_2 - \\
&\qquad\qquad 8\beta_2\,\eta_3\,\theta_2 + 2\delta\,\theta\eta_2\,\eta_3\,\theta_2 + 8\alpha_2\,\eta_5\,\theta_2 - 2\delta \\
&\qquad\qquad \theta\eta_5^2\,\theta_2 + 4\eta_2\,\eta_3\,\theta_1\,\theta_2 - 4\eta_4\,\eta_5\,\theta_1\,\theta_2))\Big)\Big)\Big)\Big\},
\end{aligned}
$$

$$
\begin{aligned}
&\Big\{\lambda_4 \to -\frac{1}{8k^2} \\
&\quad \Big(-4k^2\, r + \sqrt{\Big(16k^4\, r^2 + 16k^2\Big(-4k\,\gamma 2 - 8k\,\alpha_2 - 4k\,\beta_2 + k\,\delta\,\theta\eta_2 +} \\
&\qquad k\,\delta\,\theta\eta_3 + 2k\,\eta_2\,\theta_1 + 2k\,\eta_3\,\theta_2 - \\
&\qquad \frac{1}{2}\sqrt{\big((8k\,\gamma 2 + 16k\,\alpha_2 + 8k\,\beta_2 - 2k\,\delta\,\theta\eta_2 -} \\
&\qquad\quad 2k\,\delta\,\theta\eta_3 - 4k\,\eta_2\,\theta_1 - 4k\,\eta_3\,\theta_2)^2 - \\
&\qquad\quad 16k^2\big(16\gamma 2\,\alpha_2 + 16\gamma 2\,\beta_2 + 16\alpha_2\,\beta_2 - 4\gamma 2\,\delta\,\theta \\
&\qquad\qquad \eta_2 - 4\delta\,\theta\alpha_2\,\eta_2 - 4\delta\,\theta\alpha_2\,\eta_3 - 4\delta\,\theta\,\beta_2\,\eta_3 + \\
&\qquad\qquad \delta^2\theta^2\,\eta_2\,\eta_3 + 4\delta\,\theta\alpha_2\,\eta_4 + 4\delta\,\theta\alpha_2\,\eta_5 - \delta^2\,\theta^2 \\
&\qquad\qquad \eta_4\,\eta_5 - 8\gamma 2\,\eta_2\,\theta_1 - 8\alpha_2\,\eta_2\,\theta_1 + 2\delta\,\theta\eta_2\,\eta_3 \\
&\qquad\qquad \theta_1 + 8\alpha_2\,\eta_4\,\theta_1 - 2\delta\,\theta\eta_4^2\,\theta_1 - 8\alpha_2\,\eta_3\,\theta_2 - \\
&\qquad\qquad 8\beta_2\,\eta_3\,\theta_2 + 2\delta\,\theta\eta_2\,\eta_3\,\theta_2 + 8\alpha_2\,\eta_5\,\theta_2 - 2\delta \\
&\qquad\qquad \theta\eta_5^2\,\theta_2 + 4\eta_2\,\eta_3\,\theta_1\,\theta_2 - 4\eta_4\,\eta_5\,\theta_1\,\theta_2))\Big)\Big)\Big)\Big\},
\end{aligned}
$$

$$\left\{\lambda_5 \to -\frac{1}{8k^2}\left(-4k^2 r - \sqrt{\left(16k^4 r^2 + 16k^2\left(-4k\,\gamma 2 - 8k\,\alpha_2 - 4k\,\beta_2 + k\,\delta\,\theta\eta_2 + k\,\delta\,\theta\eta_3 + 2k\,\eta_2\,\theta_1 + 2k\,\eta_3\,\theta_2 + \frac{1}{2}\sqrt{\left((8k\,\gamma 2 + 16k\,\alpha_2 + 8k\,\beta_2 - 2k\,\delta\,\theta\eta_2 - 2k\,\delta\,\theta\eta_3 - 4k\,\eta_2\,\theta_1 - 4k\,\eta_3\,\theta_2)^2 - 16k^2\left(16\gamma 2\,\alpha_2 + 16\gamma 2\,\beta_2 + 16\alpha_2\,\beta_2 - 4\gamma 2\,\delta\,\theta\,\eta_2 - 4\delta\,\theta\alpha_2\,\eta_2 - 4\delta\,\theta\alpha_2\,\eta_3 - 4\delta\,\theta\,\beta_2\,\eta_3 + \delta^2\theta^2\,\eta_2\eta_3 + 4\delta\,\theta\alpha_2\eta_4 + 4\delta\,\theta\alpha_2\,\eta_5 - \delta^2\theta^2\,\eta_4\eta_5 - 8\gamma 2\,\eta_2\theta_1 - 8\alpha_2\,\eta_2\theta_1 + 2\delta\,\theta\eta_2\,\eta_3\,\theta_1 + 8\alpha_2\,\eta_4\theta_1 - 2\delta\,\theta\eta_4^2\,\theta_1 - 8\alpha_2\eta_3\,\theta_2 - 8\,\beta_2\eta_3\,\theta_2 + 2\delta\,\theta\eta_2\,\eta_3\theta_2 + 8\alpha_2\,\eta_5\theta_2 - 2\delta\,\theta\eta_5^2\theta_2 + 4\eta_2\eta_3\,\theta_1\,\theta_2 - 4\eta_4\,\eta_5\theta_1\,\theta_2\right)\right)}\right)\right)}\right)\right\},$$

$$\left\{\lambda_6 \to -\frac{1}{8k^2}\left(-4k^2 r + \sqrt{\left(16k^4 r^2 + 16k^2\left(-4k\,\gamma 2 - 8k\,\alpha_2 - 4k\,\beta_2 + k\,\delta\,\theta\eta_2 + k\,\delta\,\theta\eta_3 + 2k\,\eta_2\,\theta_1 + 2k\,\eta_3\,\theta_2 + \frac{1}{2}\sqrt{\left((8k\,\gamma 2 + 16k\,\alpha_2 + 8k\,\beta_2 - 2k\,\delta\,\theta\eta_2 - 2k\,\delta\,\theta\eta_3 - 4k\,\eta_2\,\theta_1 - 4k\,\eta_3\,\theta_2)^2 - 16k^2\left(16\gamma 2\,\alpha_2 + 16\gamma 2\,\beta_2 + 16\alpha_2\,\beta_2 - 4\gamma 2\,\delta\,\theta\eta_2 - 4\delta\,\theta\alpha_2\,\eta_2 - 4\delta\,\theta\alpha_2\eta_3 - 4\delta\,\theta\,\beta_2\eta_3 + \delta^2\theta^2\,\eta_2\,\eta_3 + 4\delta\,\theta\alpha_2\,\eta_4 + 4\delta\,\theta\alpha_2\eta_5 - \delta^2\theta^2\,\eta_4\eta_5 - 8\gamma 2\,\eta_2\,\theta_1 - 8\alpha_2\,\eta_2\,\theta_1 + 2\delta\,\theta\eta_2\,\eta_3\theta_1 + 8\alpha_2\,\eta_4\theta_1 - 2\delta\,\theta\eta_4^2\theta_1 - 8\alpha_2\eta_3\,\theta_2 - 8\,\beta_2\eta_3\,\theta_2 + 2\delta\,\theta\eta_2\,\eta_3\,\theta_2 + 8\alpha_2\,\eta_5\theta_2 - 2\delta\,\theta\eta_5^2\,\theta_2 + 4\eta_2\,\eta_3\,\theta_1\theta_2 - 4\eta_4\eta_5\,\theta_1\,\theta_2\right)\right)}\right)\right)}\right)\right\}\right\}$$

Again, $\alpha_1 > 0, \alpha_2 < 0, \beta_1 > 0, \beta_2 < 0, \gamma_1 > 0, \gamma_2 < 0, \delta > 0, \theta > 0,$ and $\theta_1 = \theta_2 = \frac{\theta}{2}\delta$. In additions, $\eta_2 < 0$, $\eta_3 < 0$, $\eta_4 < 0$, $\eta_5 < 0$, $\frac{\eta_2}{\eta_4} > 1$ and $\frac{\eta_3}{\eta_5} > 1$.

The six optimal λs can result in one of the three possible outcomes: real & distinct, real and equal, and complex conjugate. Thus, by logical comparison, and given the assumptions that there cannot be six feasible solutions in this case, two feasible solutions from six possible solutions of *λs* are derived and selected based upon the fact that the stable adoption and diffusion path requires the concave components of the root. Thus, from six possible roots, $\lambda_1, \lambda_2, \lambda_3,$ and λ_5 yield a positive sign and would result in convex components of the root are considered inconceivable solutions and excluded. Only λ_4 and λ_6 are able to provide a negative sign. The assumption that all terms within the square root is greater than $4k^2r$ needs to be made, however. Upon deriving roots λ_4^* and λ_6^* from Det(m)=0, the system of differential equations yields the general solution

$$z_2^t(t) = A_1 e^{\lambda_4^* t} + A_2 e^{\lambda_6^* t} + z^{p_2}$$

$$z_3^t(t) = A_3 e^{\lambda_4^* t} + A_4 e^{\lambda_6^* t} + z^{p_3}$$

where

$$A_1 + A_2 + z^{p_2} = 0$$

$$A_3 + A_4 + z^{p_3} = 0$$

$\lambda_4^* A_1 + \lambda_6^* A_2 = d_2$ (d_2 is an arbitrary non-negative constant)

$\lambda_4^* A_3 + \lambda_6^* A_4 = d_3$ (d_3 is an arbitrary non-negative constant)

with $z^{p_2} \neq z^{p_3}$ (steady-state level of technologies' adoption.)

The particular integral z^{p_2} and z^{p_3} are not being derived in this study, as the focus is not on deriving analytical solutions for the adoption path $z_2^t(t)$ and $z_3^t(t)$. The fact that both $z_2^t(t)$ and $z_3^t(t)$ share a similar set of roots, the partial derivative of real and distinct roots with respect to choice variables of either $z^t(t)$ are adequate.

The right hand side (RHS) consists of two square roots; one is inside the other. With the assumption that terms within each square root are positive, in absolute values, λ_4^* is always less than λ_6^*. Consequently, only λ_6^* dominates the solution and is real and distinct. Although λ_4^* can produce the negative sign, λ_4^* can become positive and result in convex component of root when the terms within inner-square root becomes larger[15], whereas the λ_6^* is always negative[16]. Furthermore, the derivative of λ_6^* with respect to η_2, η_3, η_4, and η_5 can be derived to explain the impact of learning by doing from exact technology and learning from others on the speed of adoption.

A_1 and A_3 are equal to zero; otherwise, A_1 or A_3 would be non-stable when the convex component of λ_4^* is dominated. Thus, the optimal path is restricted to be

$$z_2^t(t) = A_2 e^{\lambda_6^* t} + z^{p_2}$$

$$z_3^t(t) = A_4 e^{\lambda_6^* t} + z^{p_3}$$

To assess the qualitative effects on the speed of adoption, comparative results can be directly obtained through the derivation of the adoption path of either $z_2(t)$ and $z_3(t)$. Only direct differentiation of the dominant roots (the speed of adoption) is obtained here. Although they are algebraically complicated and lengthy, they can be signed with

[15] The positive values within inner-square root subtract from other terms outside inner-square root but inside the outer-square root.
[16] Assume the terms within the outer-square root are greater than $4k^2r$.

minimal conditions. Accordingly, the sign of each dominant root is specified. The steady-state level of adoption with respect to key parameters has not been obtained however. Thus, the partial derivative of the real and distinct roots with respect to the choice variables[17] (only the learning mechanism in this case) of either $z^t(t)$ and their expected signs are:

Learning by doing of new technology B from previous adoption of (exact) technology B

$$
\begin{aligned}
\frac{\partial \lambda_6^*}{\partial \eta_2} = & -(\mathrm{k}(\delta\theta + 2\theta_1 + (\mathrm{k}(\delta\theta + 2\theta_1)(4\gamma 2 - 4\beta_2 - \delta\theta\eta_3 + \eta_2(\delta\theta + 2\theta_1) - 2\eta_3\theta_2))/ \\
& (\sqrt{}(\mathrm{k}^2(16\gamma 2^2 + 64\alpha_2^2 + 16\beta_2^2 + 8\gamma 2\delta\theta\eta_2 + \delta^2\theta^2\eta_2^2 - \\
& 8\gamma 2\delta\theta\eta_3 - 2\delta^2\theta^2\eta_2\eta_3 + \delta^2\theta^2\eta_3^2 + 4\delta^2\theta^2\eta_4\eta_5 + \\
& 16\gamma 2\eta_2\theta_1 + 4\delta\theta\eta_2^2\theta_1 - 4\delta\theta\eta_2\eta_3\theta_1 + 8\delta\theta\eta_4^2\theta_1 + \\
& 4\eta_2^2\theta_1^2 - 16\gamma 2\eta_3\theta_2 - 4\delta\theta\eta_2\eta_3\theta_2 + 4\delta\theta\eta_3^2\theta_2 + \\
& 8\delta\theta\eta_5^2\theta_2 - 8\eta_2\eta_3\theta_1\theta_2 + 16\eta_4\eta_5\theta_1\theta_2 + 4\eta_3^2\theta_2^2 - \\
& 8\beta_2(4\gamma 2 + \eta_2(\delta\theta + 2\theta_1) - \eta_3(\delta\theta + 2\theta_2)) - \\
& 16\alpha_2(\eta_4(\delta\theta + 2\theta_1) + \eta_5(\delta\theta + 2\theta_2))))))/ \\
& (4\sqrt{}(\mathrm{k}^2(\mathrm{k}^2\mathrm{r}^2 - 4\mathrm{k}\gamma 2 - 8\mathrm{k}\alpha_2 - 4\mathrm{k}\beta_2 + \mathrm{k}\delta\theta\eta_2 + \mathrm{k}\delta\theta\eta_3 + \\
& 2\mathrm{k}\eta_2\theta_1 + 2\mathrm{k}\eta_3\theta_2 + \\
& \sqrt{}(\mathrm{k}^2((-4\gamma 2 - 8\alpha_2 - 4\beta_2 + \delta\theta\eta_2 + \delta\theta\eta_3 + 2\eta_2\theta_1 + \\
& 2\eta_3\theta_2)^2 - 4(-4\gamma 2\delta\theta\eta_2 + \delta^2\theta^2\eta_2\eta_3 - \delta^2\theta^2 \\
& \eta_4\eta_5 - 8\gamma 2\eta_2\theta_1 + 2\delta\theta\eta_2\eta_3\theta_1 - 2\delta\theta\eta_4^2\theta_1 + \\
& 2\delta\theta\eta_2\eta_3\theta_2 - 2\delta\theta\eta_5^2\theta_2 + 4\eta_2\eta_3\theta_1\theta_2 - 4\eta_4 \\
& \eta_5\theta_1\theta_2 + 4\alpha_2(4\gamma 2 + 4\beta_2 - \delta\theta\eta_3 + \delta\theta\eta_4 + \\
& \delta\theta\eta_5 + 2\eta_4\theta_1 - \eta_2(\delta\theta + 2\theta_1) - 2\eta_3\theta_2 + \\
& 2\eta_5\theta_2) + 4\beta_2(4\gamma 2 - \eta_3(\delta\theta + 2\theta_2))))))))
\end{aligned}
$$

The sign of $\frac{\partial \lambda_6^*}{\partial \eta_2}$ becomes negative when

$\delta\theta + 2\theta_1 + |-4\beta_2 - \delta\theta\eta_3 - 2\eta_3\theta_2| > |4\gamma_2 + \eta_2(\delta\theta + 2\theta_1)|$, assuming that the terms within

[17] Signs of risk aversion and cost adjustment can be qualitatively specified, yet they are not only cumbersome to derive, but also trivial to the purpose of this study. Thus, they are not included in the partial derivatives.

the square roots of $\frac{\partial \lambda_6^*}{\partial \eta_2}$ are positive. When this condition holds, farmer adopts the new technology faster as the ability through learning by doing from use of the *exact* technology becomes greater. Similar circumstances hold in the case where learning from technology C encourages its own adoption.

Learning by doing of new technology B from previous adoption of (similar) technology C

$$
\begin{aligned}
\frac{\partial \lambda_6^*}{\partial \eta_4} = \; & -\Big(k^2 \big(4\delta\theta\eta_4\theta_1 - 4\alpha_2(\delta\theta + 2\theta_1) + \eta_5(\delta^2\theta^2 + 4\theta_1\theta_2)\big)\Big) \Big/ \\
& \Big(2\sqrt{}\Big(k^2\big((-4\gamma 2 - 8\alpha_2 - 4\beta_2 + \delta\theta\eta_2 + \delta\theta\eta_3 + 2\eta_2\theta_1 + 2\eta_3\theta_2)^2 - \\
& \quad 4\big(-4\gamma 2\delta\theta\eta_2 + \delta^2\theta^2\eta_2\eta_3 - \delta^2\theta^2\eta_4\eta_5 - 8\gamma 2\eta_2\theta_1 + \\
& \quad 2\delta\theta\eta_2\eta_3\theta_1 - 2\delta\theta\eta_4^2\theta_1 + 2\delta\theta\eta_2\eta_3\theta_2 - 2\delta\theta\eta_5^2\theta_2 + \\
& \quad 4\eta_2\eta_3\theta_1\theta_2 - 4\eta_4\eta_5\theta_1\theta_2 + 4\alpha_2(4\gamma 2 + 4\beta_2 - \delta\theta \\
& \quad \eta_3 + \delta\theta\eta_4 + \delta\theta\eta_5 + 2\eta_4\theta_1 - \eta_2(\delta\theta + 2\theta_1) - 2 \\
& \quad \eta_3\theta_2 + 2\eta_5\theta_2) + 4\beta_2(4\gamma 2 - \eta_3(\delta\theta + 2\theta_2))\big)\big)\Big)\Big) \\
& \sqrt{}\Big(k^2\big(k^2 r^2 - 4k\gamma 2 - 8k\alpha_2 - 4k\beta_2 + k\delta\theta\eta_2 + k\delta\theta\eta_3 + \\
& \quad 2k\eta_2\theta_1 + 2k\eta_3\theta_2 + \\
& \quad \sqrt{}\big(k^2((-4\gamma 2 - 8\alpha_2 - 4\beta_2 + \delta\theta\eta_2 + \delta\theta\eta_3 + 2\eta_2\theta_1 + \\
& \quad 2\eta_3\theta_2)^2 - 4(-4\gamma 2\delta\theta\eta_2 + \delta^2\theta^2\eta_2\eta_3 - \delta^2\theta^2 \\
& \quad \eta_4\eta_5 - 8\gamma 2\eta_2\theta_1 + 2\delta\theta\eta_2\eta_3\theta_1 - 2\delta\theta\eta_4^2\theta_1 + \\
& \quad 2\delta\theta\eta_2\eta_3\theta_2 - 2\delta\theta\eta_5^2\theta_2 + 4\eta_2\eta_3\theta_1\theta_2 - 4\eta_4 \\
& \quad \eta_5\theta_1\theta_2 + 4\alpha_2(4\gamma 2 + 4\beta_2 - \delta\theta\eta_3 + \delta\theta\eta_4 + \\
& \quad \delta\theta\eta_5 + 2\eta_4\theta_1 - \eta_2(\delta\theta + 2\theta_1) - 2\eta_3\theta_2 + \\
& \quad 2\eta_5\theta_2) + 4\beta_2(4\gamma 2 - \eta_3(\delta\theta + 2\theta_2)))))\big)\big)\Big)\Big)
\end{aligned}
$$

The negative sign of $\frac{\partial \lambda_6^*}{\partial \eta_4}$ is achieved when

$\left|-4\alpha_2(\delta\theta + 2\theta_1)\right| > \left|4\delta\theta\eta_4\theta_1 + \eta_5(\delta^2\theta^2 + 4\theta_1\theta_2)\right|$, assuming that the terms within all the square roots of $\frac{\partial \lambda_6^*}{\partial \eta_4}$ are positive. When this condition holds, the farmer adopts the new technology faster when the ability to learn by doing from use of the *similar* technology of farmers becomes greater. Similar circumstances hold in the case where learning from technology B encourages the adoption of technology C.

The firm transfers one unit of the quasi-fixed factor *z* from the old technology to either the new technologies, *B* or *C*, when $\alpha_1 < \beta_1$; $\alpha_1 < \gamma_1$; $|\alpha_2| < |\beta_2|$; $|\alpha_2| < |\gamma_2|$.

Whether the firm transfers one unit of the quasi-fixed factor *z* from the new technology *B* to new technology *C* and vice versa depends upon the magnitude of $|\beta_2|$ and $|\gamma_2|$. There are two scenarios: first, profit could increase when transferring one unit of the quasi-fixed factor *z* from the new technology *B* to new technology *C,* when $\beta_1 < \gamma_1$ and $|\beta_2| < |\gamma_2|$; and second, profit could increase when transferring one unit of the quasi-fixed factor *z* from the new technology *C* to new technology *B,* when $\gamma_1 < \beta_1$ and $|\gamma_2| < |\beta_2|$.

Finally, since λ_6^* is negative, the absolute value of $\frac{\partial \lambda_6^*}{\partial \eta_2}$, $\frac{\partial \lambda_6^*}{\partial \eta_3}$, $\frac{\partial \lambda_6^*}{\partial \eta_4}$, and $\frac{\partial \lambda_6^*}{\partial \eta_5}$ increases, as η_j increases (*j=2,3,4,5*), so that the firm adopts the new technologies faster when the learning ability of the firm's manager toward either exact or similar of new technologies becomes greater.

While the derivations presented here are cumbersome and not elegant, some interesting observations can be made about the results. First, depending on the efficiency of the learning processes, the new technologies B and C can replace the traditional one A. Second, the relative learning of each new technology affects their individual and aggregate adoption. Third, depending on the relative efficiency of each learning process, it is possible to reverse the adoption of one of the new technologies, say B, in favor of increasing the adoption of the other, C. Hence, depreciation of a new technology B can happen through own and cross learning and through advancement of the alternative new technology C. These results would be counter-intuitive in the absence of considering the adoption of the two new technologies jointly and their cross-learning effects.

The most significant insight obtained through the theoretical developments in this chapter however is an indirect one. Derivations here demonstrate that as one attempts to add relevancy to our theoretical constructs of adoption decisions and account for technology interdependencies, learning and other relevant effects, the complexity of the theoretical derivations increases and solutions become quickly intractable. This result suggests that empirical analysis might be all that much more important, or may be the only way to examine relevant complexity in innovation adoption and diffusion.

Chapter 4

Adoption of Cotton Biotechnologies in the US

The hypotheses developed in chapters 1 and 2 are empirically tested in this chapter. An empirical adoption model is structured in accordance with the theoretical developments in chapter 3 and presented here.

Various learning mechanisms are explicitly modeled in the adoption models presented here. They include learning by doing from the technology of interest and from similar ones as well as learning from neighbors. The inclusion of previous year's adoption intends to capture the partial nature of the adoption process and the impact of the farmer's own experiences. It is hypothesized that the previous year's adoption of the biotech cotton variety considered (exact technology) positively influences its future adoption.

Previous year adoption of a similar biotech cotton variety captures the partial process of learning that occurs from use of similar technologies. It is hypothesized that previous year adoption of a biotech cotton variety positively influences subsequent adoptions of similar biotech cotton technologies. Furthermore, it is expected that the impact of learning from the exact technology on its rate of adoption will be greater than that of learning from a similar technology.

In addition to their own experiences, cotton growers can also learn from their neighbors or others. This type of learning is particularly important in the early stage of adoption when experience from learning by doing is limited. Average percent adoption at the county level is used as an empirical proxy of learning from others in this adoption model. It is hypothesized that the aggregate adoption of biotech cotton in a given county positively influences next year's adoption of individual farmers in the same county; then an individual adoption of the same GM cotton also increases.

In any given year, cotton growers have to decide which type of cotton varieties will be planted, both conventional and biotech. Although each variety can substitute for any other, closer traits are more likely to show higher substitutability, while varieties with different traits may show less. For instance, Bollgard® and Roundup Ready® cotton appeal to rather different groups of farmers as Bollgard® is attractive to the cotton growers who anticipated outbreak of bollworm or budworm, while Roundup Ready® is attractive to farmers who look for simple weed. These two traits should, in principle, demonstrate less, except of course that which is evident for land competition. Stacked cotton carries combines the traits of both Bollgard® and Roundup Ready® cotton. Hence, Stacked cotton is expected to substitute strongly both Bollgard® and Roundup Ready®.

Herbicide tolerance complements minimum tillage practice adoption and vice versa. It is hypothesized that if the adoption of herbicide tolerant varieties increases, then the adoption of minimum tillage practices also increase. Conversely, it is also hypothesized that if adoption of minimum tillage practices increases, then the adoption of herbicide tolerant varieties should also increase.

In addition to minimum tillage practices, the use of irrigation systems is also hypothesized to encourage the adoption of biotech cotton as they may contribute to the use of such irrigation systems earlier and more efficiently.

Unlike most agricultural innovation that are scale biased, insect resistant, and herbicide-tolerant, cotton varieties are perfectly divisible and are hypothesized to be scale neutral. Hence, any firm size variable included in the model is not anticipated to have a significant impact on the farmer's adoption decision.

Fundamentally, biotech cotton is a labor saving technology. Although pest control effectiveness is the key benefit of biotech cotton varieties, this level of effectiveness is comprised of both direct and indirect effects. The proxy of direct effect is perceived cost savings from labor and equipment efficiencies (including fuel, repairs, and maintenance).

Indirect effects from biotech cotton adoption include the technology's implied reduction in production risks, simplicity of agronomic practices, as well as the "peace of mind," convenience, and flexibility in operations. Such effects can be significant but are mostly non pecuniary in nature. Nevertheless, it is assumed that producers can place a value to such indirect effects. The higher such value is, the higher adoption will be.

It is hypothesized that if cotton growers perceive that biotech cotton is more effective than traditional practices at controlling pests, then adoption will increase. The perceived effectiveness against major and minor insects are tested in the case of Bollgard. The effectiveness of Roundup Ready against major and minor weeds is also considered. In the Stacked case, only the main pests are tested, so $M=1$ is main insect and $M=2$ is main weed.

Insect resistant biotechnologies might also have a secondary positive effectiveness impact through preservation of beneficial insects. Beneficial insects can aid in controlling harmful insect populations. It is hypothesized that if cotton growers perceive a positive impact to the beneficial insect population, then adoption of Bollgard cotton will increase.

The Empirical Model

Following these arguments, I specify here an adoption model to guide the empirical analysis. Producer adoption decisions for the various agrobiotechnologies and related agronomic practices are represented by a system of simultaneous equations. Adoption decisions are interdependent and simultaneous, as the technologies considered can be adopted both independently and as bundles. Accordingly, the following simultaneous equation system is specified and estimated.

$$\begin{aligned} Y_{i,t}^{j} = a_0^{j} + a_1^{j} Y_{i,t-1}^{j} + \sum_{j \neq \tilde{j}} a_2^{\tilde{j}} Y_{i,t-1}^{\tilde{j}} + a_3^{j,k_3} X_{3,i,t-1}^{j,k_3} + \sum_{j \neq j_4} a_4^{j,j_4} Y_{i,t}^{j,j_4} + a_5^{j,k_5} X_{5,i,t}^{j,k_5} + \sum_{k_6} a_6^{j,k_6} X_{6,i,t}^{j,k_6} + \\ a_7^{j,k_7} X_{7,i,t}^{j,k_7} + \sum_{k_8} a_8^{j,k_8} X_{8,i,t}^{j,k_8} + \sum_{k_9} a_6^{j,k_9} X_{6,i,t}^{j,k_6} + \sum_{k_{10}} a_{10}^{j,k_8} X_{10,i,t}^{j,k_{10}} + \varepsilon_{i,t}^{j} \end{aligned}$$

Where:

j = BG, RR, ST, MinTL

$\tilde{j} = \tilde{BG}, \tilde{RR}, \tilde{ST}$

i = 1, 2, ..., 703 cotton growers

t = 1999[18]

[18] Similar specification was used in other sets of survey with *t=2000* and *2001;* however, these two surveys lack the completeness of data in other key variables; consequently, empirical results were dropped in the final stage.

The dependent variable represents land allocation in period t to the three agrobiotechnologies and reduced tillage. Dynamic learning effects are explicitly modeled through the inclusion of lagged dependent variables, which are intended to capture the iterative nature of the adoption process. The relevance of the hypothesized synergies with agronomic practices can be explicitly tested within this empirical model.

The impacts of perceived economic gains of the new technologies, both pecuniary and non-pecuniary, on the adoption decision of the producers are captured through three separate sets of indicators: producer perception of pest control effectiveness, cost savings, and risk reductions ("peace of mind"). In this way, their relative importance can be measured and assessed. Such indicators of perceived economic advantage are relative in the sense that they measure performance against conventional technologies, which serve as the numeraire. Through learning, perceptions become more accurate, thus further clarifying the value of experimentation.

Differences across farms -such as in size- must also be taken into account to control for their differential impacts on adoption. In this study, a quadratic function of farm size is included to allow for any scale bias in the adoption process. Two regional dummy variables are also used to control for systematic differences in pest infestations and in the limited availability of bioengineered cotton varieties in a certain area (e.g. Texas).

Table 1 lists the variables used in the empirical estimation of the adoption and clarifies their measurement.

Table 1: Variables used in empirical specifications of adoption model

Variable & H_0		Definition	Proxy
$Y_{i,t}^{j}$		Percent adoption of each GM cotton and Min.Tillage (j) by each cotton grower (i) at time t	($Y_{i,t}^{j}$ =**dependent variables**)
	$Y_{i,t}^{BG}$	Percent adoption of Bollgard cotton by each cotton grower (i) at time t	
	$Y_{i,t}^{RR}$	Percent adoption of Roundup Ready cotton by each cotton grower (i) at time t	
	$Y_{i,t}^{ST}$	Percent adoption of Stacked cotton by each cotton grower (i) at time t	
	$Y_{i,t}^{MinTL}$	Percent adoption of Min. Tillage by each cotton grower (i) at time t	
$Y_{i,t-1}^{j}$ $H_0 : a_1^j \leq 0$		Percent adoption of each GM cotton and Min.Tillage (j) by each cotton grower (i) at prior time (t-1)	Learning by doing of exact technology
	$Y_{i,t-1}^{BG}$	Percent adoption of Bollgard cotton by each cotton grower (i) at prior time (t-1)	
$H_0 : a_1^j \leq 0$	$Y_{i,t-1}^{RR}$	Percent adoption of Roundup Ready cotton by each cotton grower (i) at prior time (t-1)	
	$Y_{i,t-1}^{ST}$	Percent adoption of Stacked cotton by each cotton grower (i) at prior time (t-1)	
	$Y_{i,t-1}^{MinTL}$	Percent adoption of Min. Tillage by each cotton grower (i) at prior time (t-1)	
$Y_{i,t-1}^{\tilde{j}}$	$j \neq \tilde{j}$	Percent adoption of *other* GM cotton (j) by each cotton grower (i) at prior time (t-1)	Learning by doing of similar technologies[19]

[19] Lagged endogenous explanatory variables are used in each adoption model in two aspects: learning by doing from exact technology and learning by doing from other similar technologies. Only one lagged dependent variable is considered as the proxy of learning by doing from exact technology while two separated lagged endogenous explanatory variables are considered as proxies of learning by doing from similar technologies. The superscript ~ is just to emphasize that these variables are considered as learning from similar technologies although in adoption model specification they are simply lagged endogenous explanatory variable that are also used as the lagged dependent variable in other adoption model.

Variable & H_0		Definition	Proxy
$H_0 : \tilde{a}_2^j \leq 0$	$Y_{i,t-1}^{\tilde{BG}}$	Percent adoption of Bollgard cotton by each cotton grower (*i*) at prior time (*t-1*)	~: indicated learning from similar technology's purposes.
$H_0 : \tilde{a}_2^j \leq 0$	$Y_{i,t-1}^{\tilde{RR}}$	Percent adoption of Roundup Ready cotton by each cotton grower (*i*) at prior time (*t-1*)	
	$Y_{i,t-1}^{\tilde{ST}}$	Percent adoption of Stacked cotton by each cotton grower (*i*) at prior time (*t-1*)	
$X_{3,i,t-1}^{j,k_3}$	$j \neq MinTL$	Average county level adoption of exact technology of cotton grower *i* at time *t* at the same FIP codes	Learning from others (neighborhood effects)
$H_0 : a_3^{j,k_3} \leq 0$	$X_{3,i,t-1}^{BG,k_3}$	Average county level adoption of BG cotton of cotton grower *i* at time *t* at the same FIP codes	
	$X_{3,i,t-1}^{RR,k_3}$	Average county level adoption of Round Ready cotton of cotton grower *i* at time *t* at the same FIP codes	
	$X_{3,i,t-1}^{ST,k_3}$	Average county level adoption of Stacked cotton of cotton grower *i* at time *t* at the same FIP codes	
$Y_{i,t}^{j,j_4}$	$j \neq j_4$	Percent adoption of each GM cotton and Min.Tillage (*j*) by each of cotton grower (*i*) at time *t* ($Y_{i,t}^{j,j_3}$ =endogenous independent variables)	Multiple simultaneous effects
$H_0 : a_4^{j,j_4} \geq 0$	$j \neq j_4$ $j_{4 \neq MinTL}$	Percent adoption of Bollgard cotton by each of cotton grower *i* at time *t* in Bollgard model	
$H_0 : a_4^{j,j_4} \geq 0$	$j \neq j_4$	Percent adoption of Roundup Ready cotton by each of cotton grower *i* at time *t* in RR model	
$H_0 : a_4^{j,j_4} \geq 0$	$j \neq j_4$	Percent adoption of Stacked cotton by each of cotton grower *i* at time *t* in ST model	

Variable & H_0		Definition	Proxy
$H_0 : a_4^{j,j_4} \leq 0$	$j \neq j_4$ $j_{4 \neq BG}$	Percent adoption of Min.TL by each of cotton grower *i* at time *t* in Min.TL model	
$X_{5,i,t}^{j,k_5}$ $H_0 : a_5^{j,j_5} \leq 0$		Binary dummy variable: Having irrigated land of cotton farmer *i* at time *t* Irrigated land =1; otherwise = 0	Synergy with other agronomic practice as irrigated land (when appeared on RHS)
$X_{6,i,t}^{j,k_6}$ $H_0 : a_6^{j,k_6} = 0$	$k_6 = 1{,}2$	Average farm size of cotton grower *i* in year *t* ('000 acres)	Heterogeneity toward economy of scales
	$X_{6,i,t}^{j,k_6=1}$	size$_i$ = Total planted ('000 acres)	
	$X_{6,i,t}^{j,k_6=2}$	Size square$_i$ = size$_i^2$	
$X_{7,i,t}^{j,k_7}$ $H_0 : a_7^{j,k_7} \leq 0$	$j \neq MinTL$	Perceived labor and capital saving when adopting GM cotton over traditional varieties in dollar of cotton grower *i* at time *t*	Monetary Effect (Cost & labor savings of GM cotton adoption)
	$X_{7,i,t}^{BG,k_7}$	Perceived labor and capital saving when adopting Bollgard cotton over traditional varieties in dollar of cotton grower *i* at time *t*	
	$X_{7,i,t}^{RR,k_7}$	Perceived labor and capital saving when adopting Roundup Ready cotton over traditional varieties in dollar of cotton grower *i* at time *t*	
	$X_{7,i,t}^{ST,k_7}$	Perceived labor and capital saving when adopting Stacked cotton over traditional varieties in dollar of cotton grower *i* at time *t*	
$X_{8,i,t}^{j,k_8}$ $H_0 : a_8^{j,k_8} \geq 0$	$j \neq MinTL$ $k_8 = 1{,}2$	Perceived values toward peace of mind and convenience when cotton grower *i* adopting GM cotton over traditional varieties at time *t* in likert scales	Non-monetary effect (Peace of mind of GM cotton adoption)
	$X_{8,i,t}^{BG,k_8=1}$	Perceived values toward peace of mind and convenience	Peace of mind of Bollgard

Variable & H_0		Definition	Proxy
		when cotton grower *i* adopting Bollgard cotton over traditional varieties at time *t* in likert scales	adoption
	$X_{8,i,t}^{RR,k_8=1}$	Perceived values toward peace of mind and convenience when cotton grower *i* adopting Roundup Ready cotton over traditional varieties at time *t* in likert scales	Peace of mind of Roundup Ready adoption
	$X_{8,i,t}^{ST,k_8=1}$	Perceived values toward peace of mind and convenience when cotton grower *i* adopting Stacked cotton over traditional varieties at time *t* in likert scales	Peace of mind of Stacked adoption
$H_0 : a_8^{BG,k_8=2} \geq 0$	$X_{8,i,t}^{BG,k=2}$	Perceived impact over beneficial insect in likert scales of BG cotton grower *i* at time *t* in BG model only	Impact on beneficial insect of Bollgard adoption
$X_{9,i,t}^{j,k_9}$	$j \neq MinTL$ $k_9 = 1,2$	Perceived pest control effectiveness toward GM cotton adoption of cotton grower *i* at time *t* in likert scales	Pest control effectiveness
$H_0 : a_9^{j,k_9=M_2} \geq 0$	$X_{9,i,t}^{BG,k_9=1}$	Perceived major insect control effectiveness toward Bollgard cotton adoption of cotton grower *i* at time *t* in likert scales	
$H_0 : a_9^{j,k_9=M_2} \geq 0$	$X_{9,i,t}^{BG,k_9=2}$	Perceived minor insect control effectiveness toward Bollgard cotton adoption of cotton grower *i* at time *t* in likert scales	
	$X_{9,i,t}^{RR,k_9=1}$	Perceived major weed control effectiveness toward Roundup Ready cotton adoption of cotton grower *i* at time *t* in likert scales	
	$X_{9,i,t}^{RR,k_9=2}$	Perceived minor weed control effectiveness toward Roundup Ready cotton adoption of cotton grower *i* at time *t* in likert scales	

Variable & H_0		Definition	Proxy
	$X_{9,i,t}^{ST,k_9=1}$	Perceived major insect control effectiveness toward Stacked cotton adoption of cotton grower *i* at time *t* in likert scales	
	$X_{9,i,t}^{ST,k_9=2}$	Perceived major weed control effectiveness toward Stacked cotton adoption of cotton grower *i* at time *t* in likert scales	
$X_{10,i,t}^{j,k_{10}}$	$k_{10} = 1,2$ $X_{10,i,t}^{j,k_{10}=1}$ $X_{10,i,t}^{j,k_{10}=2}$	Binary dummy variables whether cotton grower *i* at year *t* was located at $k_{10} = 1$: Texas =1; otherwise =0 $k_{10} = 2$: Southern region (Louisiana and Mississippi) =1; otherwise =0	Locational effect
Restrictions in Minimum Tillage model:		$a_1^j, a_2^j, a_7^j . a_8^j, a_9^j = 0$	

Expected Signs of Coefficient Estimates and Hypothesis Testing

Based on the arguments developed before, the stated hypotheses can be statistically tested as follows:

- Learning mechanisms
  - Learning by doing from exact technology

: $H_0 : a_1^j \leq 0$

$H_1 : a_1^j > 0$

  - Learning by doing from similar technologies

: $H_0 : a_2^{\tilde{j}} \leq 0 \qquad (j \neq \tilde{j})$

$H_1 : a_2^{\tilde{j}} > 0 \qquad (j \neq \tilde{j})$

  - Learning from others (neighborhood effect)

: $H_0 : a_3^{j,k_3} \leq 0$

$H_1 : a_3^{j,k_3} > 0$

- Technology Interdependencies
  - BG model

: $H_0 : a_4^{j,j_4} \geq 0 \qquad (j \neq j_4 \;\&\; j_4 \neq MinTL)$

$H_1 : a_4^{j,j_4} < 0 \qquad (j \neq j_4 \;\&\; j_4 \neq MinTL)$

  - RR and ST models

: $H_0 : a_4^{j,j_4} \geq 0 \qquad (j \neq j_4)$

$H_1 : a_4^{j,j_4} < 0 \qquad (j \neq j_4)$

- Minimum Tillage model

: $H_0 : a_4^{j,j_4} \leq 0 \qquad (j \neq j_4 \,\&\, j_4 \neq BG)$

$H_1 : a_4^{j,j_4} > 0 \qquad (j \neq j_4 \,\&\, j_4 \neq BG)$

For instance, the hypothesis that minimum tillage encourages adoption of RR and/or ST technologies can be empirically assessed by evaluating the statistical significance of $a_4^{MinTL,RR}$ and $a_4^{MinTL,ST}$.

- Irrigation system

$H_0 : a_5^{j,j_5} \leq 0$

$H_1 : a_5^{j,j_5} > 0$

- Farm heterogeneity and scale effects

: $H_0 : a_6^{j,k_6} = 0$

$H_1 : a_6^{j,k_6} \neq 0$

- Perceived economic advantages of biotechnologies

  - Direct, pecuniary effects

: $H_0 : a_7^{j,k_7} \leq 0 \qquad (j \neq MinTL)$

$H_1 : a_7^{j,k_7} > 0 \qquad (j \neq MinTL)$

  - Indirect, non-pecuniary effects (Peace of mind and convenience)

: $H_0 : a_8^{j,k_8} \geq 0 \qquad (j \neq MinTL)$

$H_1 : a_8^{j,k_8} < 0$ [20] $\qquad (j \neq MinTL)$

  - Pest control effectiveness

[20] The likert scale used in the survey values lower numbers (such as 1) as superior to non-GM cotton, while higher the numbers (such as 5) are inferior to non-GM cotton. Thus, the alternate hypothesis follows a left-tailed *t* test.

: $H_0 : a_9^{j,k_9=M_2} \geq 0$ ($j \neq MinTL$ and $M_2=1,2$)

$H_1 : a_9^{j,k_{=2}=M_2} < 0$[21] ($j \neq MinTL$ and $M_2=1,2$)

- Impact on beneficial insect

: $H_0 : a_8^{BG,k_8=2} \geq 0$

$H_1 : a_8^{BG,k_{=2}} < 0$[22]

Effectiveness against both major and minor insects are tested in Bollgard using *M=1* and *M=2*, respectively. Effectiveness against major and minor weeds are tested in the in Roundup Ready case through similar methods. In the Stacked case, only effectiveness against major pests is included, so *M=1* is major insects, and *M=2* is major weeds.

Data

In order to estimate the proposed adoption model above, I use producer-survey data. In order to capture the rich substitution effects among the three cotton biotechnologies, adoption data was sought for the years where BG adoption was still increasing and ST was coming into the market. In more recent years, RR and ST technologies have dominated adoption patterns, while BG adoption has diminished, probably due to substitution (Figure 1). Several market research companies were contacted for such data availability and an appropriate dataset was located. The survey used includes cotton

[21] The likert scale used in the survey values lower numbers (such as 1) as "much better" pest control, while the higher numbers (such as 4) are "not nearly as good" pest control compared to non-GM cotton. Thus, the alternate hypothesis follows left-tailed *t* test.

[22] The likert scale used in the survey values lower numbers (such as 1) as "very satisfied", while the higher numbers (such as 4), are "very dissatisfied" with the performance of Bollgard cotton. Thus, the alternate hypothesis follows a left-tailed *t* test.

growers from all cotton growing states[23] except California and Arizona and it was conducted in 1999. The survey was conducted by the marketing firm Marketing Horizons, Inc. Data from this survey were contributed from Marketing Horizons for the purpose of this research. There are 703 usable observations, of which 564 and 139 observations involve biotech cotton adopters[24], and non-adopters[25], respectively. Due to the confidentiality nature of data in the study, descriptive statistics can not be shown.

Although most key variables are derived from this survey, two other sources of data were used. Certain information on tillage practices was obtained from the Conservation Technology Information Center (CTIC). Similarly, information on aggregate adoption of the three biotech cotton varieties (total acres) for each county was obtained from the trait supplier for the purpose of this research. CTIC provides data on minimum tillage use at the county level, while the total biotech cotton acres for each county are utilized to derive average percent adoption of each biotechnology cotton trait at the county level.

Econometric Estimation

The data suffers from heteroscedasticity and the errors are not normally distributed. Additionally, when the four equations are estimated simultaneously, the dependent variable of each equation also appears as an explanatory variable on the right

[23] The survey consists of samples in the following states: Alabama, Arkansas, Florida, Georgia, Louisiana, Missouri, Mississippi, North Carolina, New Mexico, Oklahoma, South, Carolina, Tennessee, Texas, and Virginia.
[24] Users were defined as having planted more than 50 acres of any genetically modified cotton in 1999
[25] Non-users were defined as having planted less than 50 acres of any genetically modified cotton in 1999

hand side. Thus, OLS would result in simultaneity bias and inconsistent estimates. Instrumental variable (IV) estimators or maximum likelihood (MLE) approaches are thus preferable. IV estimators rely on effective instrument selection, while MLE assumes the errors are normally distributed.

For IV estimators, under conditional homoscedasticity, the multiple-equation system estimated via a Generalized Method of Moment (GMM)[26] reduces to the full information instrumental variable efficient estimator, which in turn reduces to 3SLS if the set of instrumental variables is common to all equations in the system. If more restrictions are imposed in such a way that all the regressors are predetermined, then 3SLS reduces to seemingly unrelated regressions (SUR) (Hayashi, 2000).

To choose the most preferable among IV estimators, one first must determine whether the model is identified, unidentified, or over-identified. Thus, the number of free elements in the covariance matrix and the numbers of parameters to be estimated are compared. Specifically, if the number of parameters equals the number of free elements in the covariance matrix, then there may exist a unique set of parameter estimates that exactly reproduce the observed covariance matrix. In this case, the model is said to be just identified or saturated. If the number of parameters is less than the number of free elements in the covariance matrix, there may exist no set of parameter estimates that reproduces the observed covariance matrix. In this case, the model is said to be overidentified. In the (exactly) identified case, 2SLS and GMM produce the same results (Johnston and John, 1997).

[26] The following references are excellent sources for interesting readers on the mathematical rigors of GMM (Hall, 1993; Hansen, 1982; Hansen and Kenneth, 1982; Hayashi, 2000; Green, 1997; Matyas, 1999). For SAS codes and estimation method, see SAS (2001).

In the overidentified case, only the GMM produces consistent estimates, regardless of the weighting matrix used. When optimal weighting matrix is selected as the inverse of the asymptotic variance matrix of the orthogonality conditions of moment condition, GMM also produces efficient estimates (Mullin, 2003[a], SAS (2001). There are two methods for improving the efficiency of the parameter estimates in the presence of heteroscedastic errors. If the error variance relationships are known, weighted regression can be used or an error model can be estimated. If the error variance relationship is unknown, GMM estimation can be used.

Furthermore, among IV estimators in a system of equations, GMM requires the least assumptions toward the distribution of the data. GMM, however, requires correct model specification and large sample sizes. A sample size of 703 observations is considered adequate. So, given all relevant considerations, I use GMM for the empirical estimation of the adoption model. However, to confirm the robustness of the model and examine the sensitivity of the results to alternate estimation methods, some additional considerations were necessary.

An alternative method to the GMM is maximum likelihood. Fundamentally, MLE has some desirable properties relative to GMM in at least two areas. First, when the distributional assumptions are valid, the MLE provides the most efficient parameter estimates,[27] while the GMM method may not. Second, MLE doesn't require specification of instruments. Although both IV estimators and maximum likelihood methods are theoretically justified, MLE would be preferred if the properties required by MLE were met.

[27] The asymptotic variance of MLE is usually equal to the Cramer-Rao lower bound – the lowest asymptotic variance that a consistent estimator can have (Kennedy (1997), pp. 30.)

That said, MLE requires both complete specification of the model and strong distributional assumptions. To make the estimation problem tractable, the assumed distributions often must be serially uncorrelated and conditionally homoscedastic. When the distributional assumptions are not satisfied, like in this case, the parameters estimates may be biased even in large samples. These limitations of MLE restrict the scope. Nevertheless, MLE is also used here to evaluate the robustness of the estimated model.

Table 2: Empirical results of BG adoption model

GM Cotton 99 Adoption Model	**Bollgard® model (BG)**			
Proxy and meaning of explanatory variables	Parameter Estimated	Aprrox. Std. Error	t-Value	Pr > |t|
Dependent variable: %BG$_{99}$ per farmer				
Intercept_BT	0.985	0.086	11.460	<.0001
Learning mechanisms				
Learning by doing of exact technology	0.250	0.031	8.160	<.0001
Learning by doing of similar technologies				
Learning by doing from last year RR	0.030	0.011	2.720	0.007
Learning by doing from last year ST	0.034	0.018	1.890	0.059
Learning from others	0.132	0.034	3.860	0.000
Multiple simultaneous effects				
With RR adoption	-0.028	0.021	-1.330	0.183
With ST adoption	-0.071	0.026	-2.750	0.006
Synergies with other agronomic practices				
Synergies with irrigation	0.047	0.027	1.730	0.084
Heterogeneity toward economies of scale				
Scale bias	-0.001	0.020	-0.030	0.975
Quadratic scale bias	0.000	0.007	0.060	0.953
Monetary effects				
Labor and capital savings	0.004	0.001	4.650	<.0001
Non-monetary effects				
Values toward peace of mind & convenience	0.007	0.017	0.430	0.667
Pest control effectiveness				
Major Insect control effectiveness	-0.099	0.025	-3.970	<.0001
Minor Insect control effectiveness	-0.071	0.029	-2.400	0.017
Secondary control over nontarget pest				
Impact over beneficial insect	-0.123	0.012	-10.32	<.0001
Locational effects				
For Texas state	-0.003	0.009	-0.320	0.750
For southern region (Louisiana and Mississippi)	0.028	0.023	1.220	0.223

Table 3: Empirical results of RR adoption model

GM Cotton 99 Adoption Model	**Roundup Ready® model (RR)**			
Proxy and meaning of explanatory variables	Parameter Estimated	Aprrox. Std. Error	t-Value	Pr > |t|
Dependent variable: %RR_{99} per farmer				
Intercept_RR	0.958	0.081	11.830	<.0001
Learning mechanisms				
Learning by doing of exact technology	0.260	0.034	7.550	<.0001
Learning by doing of similar technologies				
Learning by doing from last year BG	0.070	0.022	3.240	0.001
Learning by doing from last year ST	0.141	0.027	5.270	<.0001
Learning from others	0.059	0.034	1.720	0.086
Multiple simultaneous effects				
With BG adoption	-0.108	0.036	-3.000	0.003
With ST adoption	-0.283	0.041	-6.950	<.0001
Synergies with other agronomic practices				
Synergies with minimum tillage program	0.491	0.086	5.680	<.0001
Synergies with irrigation	0.086	0.023	3.750	0.000
Heterogeneity toward economies of scale				
Scale bias	-0.057	0.028	-2.030	0.042
Quadratic scale bias	0.009	0.008	1.200	0.232
Monetary effects				
Labor and capital savings	0.000	0.001	-0.170	0.868
Non-monetary effects				
Values toward peace of mind and convenience	-0.099	0.016	-6.240	<.0001
Pest control effectiveness				
Major Insect control effectiveness	-0.073	0.015	-4.770	<.0001
Minor Insect control effectiveness	-0.106	0.022	-4.830	<.0001
Locational effects				
For Texas state	-0.018	0.023	-0.790	0.430
For southern region (Louisiana and Mississippi)	-0.045	0.016	-2.810	0.005

Table 4: Empirical results of ST adoption model

GM Cotton 99 Adoption Model	**Bollgard® Roundup Ready® model (ST)**			
Proxy and meaning of explanatory variables	Parameter Estimated	Aprrox. Std. Error	t-Value	Pr > |t|
Dependent variable: %ST_{99} per farmer				
Intercept_St	0.976	0.058	16.73	<.0001
Learning mechanisms				
Learning by doing of exact technology	0.308	0.042	7.27	<.0001
Learning by doing of similar technologies				
Learning by doing from last year BG	0.207	0.031	6.71	<.0001
Learning by doing from last year RR	0.191	0.033	5.89	<.0001
Learning from others	0.110	0.084	1.32	0.1879
Multiple simultaneous effects				
With BG adoption	-0.290	0.049	-5.92	<.0001
With RR adoption	-0.367	0.074	-4.93	<.0001
Synergies with other agronomic practices				
Synergies with minimum tillage program	0.306	0.176	1.74	0.0817
Synergies with irrigation	0.129	0.020	6.51	<.0001
Heterogeneity toward economies of scale				
Scale bias	-0.010	0.024	-0.4	0.6859
Quadratic scale bias	0.001	0.006	0.13	0.8985
Monetary effects				
Labor and capital savings	0.006	0.001	4.19	<.0001
Non-monetary effects				
Values toward peace of mind and convenience	-0.042	0.018	-2.31	0.0211
Pest control effectiveness				
Major insect control effectiveness	-0.136	0.014	-10.02	<.0001
Major weed control effectiveness	-0.112	0.019	-6.05	<.0001
Locational effects				
For Texas state	-0.030	0.022	-1.37	0.1716
For southern region (Louisiana and Mississippi)	-0.011	0.025	-0.45	0.6508

Table 5: Empirical results of minimum tillage adoption model:

GM Cotton 99 Adoption Model	**Minimum Tillage Practices**			
Proxy and meaning of explanatory variables	Parameter Estimated	Aprrox. Std. Error	t-Value	Pr > |t|
Dependent variable: %MinTL$_{99}$ per farmer				
Intercept_MinTL	-0.044	0.023	-1.93	0.0546
Learning mechanisms				
Learning from others	0.062	0.019	3.36	0.0008
Synergies with other agronomic practices				
Synergies with RR varieties	0.345	0.041	8.43	<.0001
Synergies with ST varieties	0.220	0.033	6.64	<.0001
Synergies with RR Irrigation	0.001	0.027	0.05	0.9607
Synergies with ST Irrigation	-0.022	0.019	-1.15	0.2523
Heterogeneity toward economies of scale				
Scale bias	0.021	0.033	0.64	0.5247
Quadratic scale bias	-0.002	0.009	-0.18	0.8552
Locational effects				
For Texas state	-0.043	0.018	-2.45	0.0145
For southern region (Louisiana and Mississippi)	-0.013	0.015	-0.9	0.367

Empirical Results

The parameter estimates presented in tables 2-5 are based on GMM estimation. The empirical model also estimated using alternative econometric methods including 3SLS and MLE. The results from all three estimation procedures were similar. Due to the advantages of GMM over other methods, particularly in the over-identified case, and the remedies for heteroscedasticity and endogeneity with consistent and efficient estimates, the GMM results are presented here.

Overall, innovation adoption is driven by the learning process. All GM crops substitute one another for land. Synergies between biotech cotton and other agronomic practices, including minimum tillage and irrigation are strong. This is especially true in the case of herbicide-tolerant varieties and minimum tillage practices. There is generally no scale bias, but when there is, RR is preferred by the smaller firm. Perceived economic benefits and technology effectiveness are found to have a key positive impact on adoption.

The Impacts of Learning

Learning by doing with either exact or similar technologies, that is experience from traits used in the previous year, is significant across all adoption equations. All three types of biotech cotton varieties are driven by these learning mechanisms, although experience with exact technologies is found to have a greater influence than experience from similar technologies. Learning from neighbors is also significant except in the case of ST, indicating that farmers observe and learn from other users as well. In addition to biotech cotton adoption, the adoption of minimum tillage is also influenced by learning from neighbors.[28] The fact that learning from neighbors is insignificant in the case of ST is reasonable, as information is expected to be scarce in the neighboring area due to the recent release of the ST technology. The relative significance of the three different learning mechanisms in the model suggests that learning by doing through partial adoption of the exact technology is the most influential, followed by learning from neighbors and similar technologies, depending on the type of the biotech cotton.

For instance, in the BG case learning by doing of exact technology has the strongest impact on adoption, followed by learning from others and then learning from similar technologies. On average, cotton growers would increase *Bt* adoption in period $t+1$ by 0.25% with every 1% increase in the acreage of *Bt* in period t, ceteris paribus. On average cotton growers would increase *Bt* adoption in period $t+1$ by 0.13% with a 1% increase of *Bt* adoption at the same county in period t, ceteris paribus. On average cotton growers would increase *Bt* adoption in period $t+1$ by a little more than 0.03% for every 1% increase in the previous RR (or ST) own adoption in period t, ceteris paribus.

These outcomes confirm the hypothesized effects of various learning mechanisms, in that the learning processes encourage adoption, and the magnitude of learning by doing from exact technology is the strongest such as in BG model. The effect of learning from others and from similar technologies is also confirmed.

[28] Due to data limitation, learning from own experience of minimum tillage can not be incorporated in this study.

Adoption Interdependencies and Technology Bundles

Farmers encounter multiple choices in the selection of seed, including biotech and traditional cotton seeds, which can be chosen over others simultaneously. Traits are priced differently and can substitute for one another. Thus, farmers may substitute one seed for another, according to their characteristics, and relative competitiveness for land.[29] The substitution effects, indeed, are very strong, and stronger among those varieties that shared certain characteristics. The substitutability between ST and RR was found to be the strongest.

In the BG adoption model, RR is statistically insignificant, suggesting that adoption of BG is not strongly influenced by adoption considerations for RR. In RR adoption model, BG has a significant impact. Specifically, RR adoption increases by about 10% of every 100% decrease in BG acres with all other factors held constant. In addition, RR adoption increases about 28% for every 100% decrease in ST acres with all other factors held constant. In the ST adoption model, BG and RR are significant. ST adoption increases about 29% for every 100% decrease in BG acres with all other factors held constant. Moreover, ST adoption increases 37% for every 100% decrease in RR acres with all other factors held constant. These results suggest that the last of the three biotechnologies introduced in U.S. cotton production must "wrestle" acres away from other biotechnologies for its success. Overall, the empirical results confirm strong interdependencies among the three biotechnologies.

[29] All endogenous explanatory GM cotton variables are negative in sign, implying that the substitution effect of the dependent variable. All but the RR in BG model are statistically significant at 0.01 significance level. To adopt BG, farmers may not need to reduce the RR acres.

Synergy with Agronomic Practices

Previous literature has qualitatively hypothesized that certain agronomic practices (e.g. no-tillage and irrigated land adoption) may be influenced by the use of biotech varieties and vice versa. The empirical results obtained here confirm that minimum tillage adoption influences and is influenced by herbicide tolerant cotton adoption. Synergies between minimum tillage adoption and herbicide tolerant variety adoption are very strong. For instance, on average RR or ST adoptions increase 49% and 31%, respectively, for every 100% increases in minimum tillage adoption with all other variables held constant. On the other hand, on average minimum tillage increases 35% or 22% for every 100% increase in RR or ST adoption, respectively, with all other variables held constant. The synergies between minimum tillage practice and herbicide tolerance reinforce and strengthen the adoption of one another. This study is the first to empirically confirm this synergistic relationship between herbicide tolerance and minimum tillage practices. Considering the current controversy toward adoption of biotech crops, the results here underline one of the alleged environmental benefits-- soil preservation-- of biotech cotton.

In addition to minimum tillage practice, irrigation also influences the adoption of biotech cotton varieties. The coefficient of (binary) irrigation measures the average difference in percentages adoption of each biotech cotton variety in irrigated land and non-irrigated land. Irrigated land experiences increased by BT, RR, or ST adoption (on average) 5%, 9%, or 13 % respectively, relative to non-irrigated land with all other variables held constant.

Firm Heterogeneity and Scale Bias

There is no scale bias across all GM cotton varieties or minimum tillage except in the case of RR cotton where smaller firms demonstrated higher adoption rates than larger firms. These results are consistent with the divisible nature of the technology and the lack of need for upfront investments. Hence, the stated hypothesis could not be generally rejected. It is unclear whether the minor advantage for small firms identified in the case of RR cotton is spurious or in fact a structural effect.

Perceived Economic Gains from Innovation Adoption

Pest control effectiveness is a unique characteristic inherent in biotech cotton varieties. Without appropriate pest control, yield losses lead to reductions in profit. Through biotech cotton adoption, farmers commit to a new pest control paradigm, which ultimately might minimize yield loss and increase profits. Thus, the farmers' perceptions of pest control effectiveness determine one of the perceived dimensions of innovation gains from these new technologies: reduction in risk. All the proxies of perceived pest control effectiveness and secondary control over non-target pests have the correct sign and are statistically significant at the 0.01% level throughout all adoption equations. Hence, as farmers' perceptions for decreased risk improve, their adoption tends to increase.

Perceived economic gains in the form of cost reductions are also significant. For instance, on average, *Bt* adoption increases 4% for every $10 of perceived savings in cost/acre with all other variables held constant. This impact increases to 6% for ST varieties. Such effects are not strong in the case of RR cotton. It would appear that farmers perceive RR cotton as risk reducing rather than cost reducing technology.

In all, the empirical results of the adoption model are consistent with the hypothesized effects and the theoretical development in the previous chapter. Furthermore, they tell a story of a complex adoption decision process where farmers consider interdependent technologies with strong substitutability but also synergistic relationships with other agronomic practices; where complex learning mechanisms are utilized to improve innovation pay offs; and where complex perceptions of innovation gains—both pecuniary and non-pecuniary—are considered. These complexities in adoption decisions have not been uncovered or investigated in prior adoption studies of agricultural innovations.

CHAPTER 5

DIFFUSION OF COTTON BIOTECHNOLOGIES IN THE US

The hypotheses developed in chapters 1 and 2 are empirically tested in this chapter. An empirical diffusion model is structured in accordance with the theoretical developments in chapter 3 and estimated econometrically in this chapter. It should be noted that this is not a naïve epidemic diffusion model that seeks to predict the maximum level of diffusion or its speed. Instead, this is a theoretically consistent model that investigates whether the adoption behavior of *all* biotechnology cotton adopters in the US (i.e. *of the population*) over a five year period is consistent with the stated hypotheses developed in chapters 1 and 2. Such estimation has not been attempted in the past since population data has never been available for any agricultural innovation (or to the author's knowledge any new technology of any kind). The population of adopters includes thousands of individuals located in 19 states. To keep the estimation tractable and to complete the data on adopters with additional relevant information that cannot be available for each individual in the population, I aggregate individual adoption information to the county level. Hence, the unit of observation in the analysis is the county. Estimated in this fashion, the empirical diffusion model also includes some useful considerations of space and innovation spread.

As before, three separate learning mechanisms are explicitly modeled in the diffusion models of the three biotechnology cotton varieties. They include learning by doing from the technology of interest (learning from exact technology), learning from a similar technology, and learning from others. However, all three learning variables take a somewhat different meaning when the unit of observation is the county rather than the individual adopter.

The inclusion of lagged dependent variables intends to capture the iterative nature of the adoption process at the county level. It is hypothesized that previous adoption of the same biotech cotton variety positively influences future adoption of the same technology. The inclusion of lagged adoption of a similar biotech cotton variety in the same area intends to capture the concept that adopters could learn from similar technologies as well. Furthermore, it is hypothesized that the magnitude of learning from the exact technology is greater than from similar technologies in the same area. It should be noted here that at the county level experience from using the new technology becomes a hybrid concept that combines learning by doing and learning from neighbors that are most proximate.

Learning from others also takes a somewhat different meaning within the context of the diffusion model. Once again, I seek to quantify the impact of any learning from proximity effect on adoption. Proximity for this larger space model has a different context.

Specifically, I quantify the "learning from others" effect through the combination of two distinct influences of learning: spatial distance to the source of information and quality of information where only successful adopters matter. These concepts serve as the basic framework for constructing the proxy of learning from others (neighborhood effect) in the diffusion model. The idea is to incorporate only the successful adopters in the aggregate adoption model as "sources of information". Arbitrarily 25% adoption is used as a threshold to divide successful and unsuccessful areas of adoption.[30] After the sources of information were determined, the distances between each unit of analysis (county) and sources of information were calculated. Only the nearest county is selected; consequently, the distances between the unit of analysis and the source of information are used as the first of two parts of learning from others in the diffusion model.

It is possible that several sources of information around the area of analysis are adjacent to one another. The previous proxy would only account for the closest sources of information and discard the rest. To take other nearby sources of information into consideration, the numbers of sources of information must be taken into account. An ad hoc method is to count the sources of information; however, far away counties are not likely to influence the diffusion phenomena comparing to nearby counties. The question is how far away is considered "nearby" and how far away is counted as "far". If the closer sources of information are to be given more weight, it may be appropriate to take variance into account. These factors would complicate the counting since each source of information may not be counted as one, but more or less depending upon their weight. Another possibility is to introduce a fixed radius around the area of analysis and count all the sources of information within this radius.

Instead of choosing a fixed radius, flexible boundaries can be calculated based upon their relative distance to all other sources of information in order to count all the sources of information that are located within this boundary. The later method relies on the relative distances and location of the unit of analysis and whether it is located in an area of high concentration to other sources or a rather isolated area. This later method is used in this analysis, and average distances from all sources of information are used as

[30] For Bollgard Cotton, 25% adoption was about 10% of total GM cotton planted in 1996.

the boundary. Thus, the number of sources of information that are located between the area of analysis and all the sources of information determine the second proxy of learning from others in the empirical diffusion model.

It is hypothesized that as the area of analysis and the source of information become closer in distance, more information is shared and the adoption rate increases. It is further hypothesized that the more sources of information within the boundary, the more information is shared, and the larger the adoption rate.

Biotech and traditional cotton varieties compete for land; thus, it is hypothesized that biotech cotton varieties are substitutes. The magnitude of substitution is expected to be stronger between biotech cotton varieties that have similar traits than when they do not.

The relevance of the hypothesized synergies between herbicide tolerant cotton varieties and agronomic practices, such as minimum tillage, can be explicitly tested within the empirical model. Synergies with other agronomic practices are also considered. Irrigated land is hypothesized to encourage the adoptions of biotech cotton due to implied efficiency gains.

Once again, the scale neutrality of cotton biotechnologies is empirically evaluated. Insect resistant and herbicide tolerant cotton varieties as well as minimum tillage practices are hypothesized to be scale neutral.

The various counties in different locations are assumed to be heterogeneous in the pest pressure they experience. Accordingly, locations are differentiated by measures of both insect and weed pressures. The higher the pest pressures are, the higher the adoption and diffusion of biotech cotton varieties are expected to be.

The Empirical Model

Following these arguments, I specify here diffusion model to guide the empirical analysis. The adoption decisions for the various agrobiotechnologies and related agronomic practices are represented by a system of simultaneous equations for a period of five years. Adoption decisions are interdependent and simultaneous, as the three biotechnologies can be adopted both independently and as bundles. Accordingly, the following simultaneous equation system is specified and estimated.

$$Y_{i,t}^{j} = a_0^{j} + a_1^{j} Y_{i,t-1}^{j} + \sum_{j \neq \tilde{j}} a_2^{\tilde{j}} Y_{i,t-1}^{\tilde{j}} + \sum_{j \neq j_3} a_3^{j,j_3} Y_{i,t}^{j,j_3} + \sum_{k_4} a_4^{j,k_4} X_{4,i,t}^{j,k_4} + \sum_{k_5} a_5^{j,k_5} X_{5,i}^{j,k_5} + \sum_{k_6} a_6^{j,k_6} X_{6,t}^{j,k_6} +$$

$$\sum_{k_7} a_7^{j,k_7} X_{7,i_s,t}^{j,k_7} + \sum_{k_8} a_8^{j,k_8} X_{8,i,t}^{j,k_8} + \varepsilon_{i,t}^{j}$$

Where:

j = BG, RR, ST, MinTL

$\tilde{j} = \tilde{BG}, \tilde{RR}, \tilde{ST}$

i = 1, 2, ..., 720 counties

i_s *= 1, 2, ...,19* states

t = 1996, 1997, 1998, 1999, 2000

Table 6: Variables used in empirical specification of diffusion model

Variable		Definition	Proxy
$Y_{i,t}^{j}$		Percent adoption of each biotech cotton and Min.Tillage (*j*) by each county (*i*) at time *t*	($Y_{i,t}^{j}$ =dependent variables)
	$Y_{i,t}^{BG}$	Percent adoption of Bollgard cotton by each county (*i*) at time *t*	
	$Y_{i,t}^{RR}$	Percent adoption of Roundup Ready cotton by each county (*i*) at time *t*	
	$Y_{i,t}^{ST}$	Percent adoption of Stacked cotton by each county (*i*) at time *t*	
	$Y_{i,t}^{MinTL}$	Percent adoption of Min. Tillage by each county (*i*) at time *t*	
$Y_{i,t-1}^{j}$		Percent adoption of each biotech cotton and Min.Tillage (*j*) by each county (*i*) at prior time (*t-1*) (one year lagged dependent variables)	Learning by doing of exact technology
$H_0 : a_1^j \le 0$	$Y_{i,t-1}^{BG}$	Percent adoption of Bollgard cotton by each county (*i*) at prior time (*t-1*)	
	$Y_{i,t-1}^{RR}$	Percent adoption of Roundup Ready cotton by each county (*i*) at prior time (*t-1*)	
	$Y_{i,t-1}^{ST}$	Percent adoption of Stacked cotton by each county (*i*) at prior time (*t-1*)	
	$Y_{i,t-1}^{MinTL}$	Percent adoption of Min. Tillage by each county (*i*) at prior time (*t-1*)	
$Y_{i,t-1}^{\tilde{j}}$	$j \neq \tilde{j}$	Percent adoption of *other* biotech cotton ($\tilde{j}$) by each county (*i*) at prior time (*t-1*)	Learning by doing of similar technologies[31]
$H_0 : a_2^{\tilde{j}} \le 0$	$Y_{i,t-1}^{\tilde{BG}}$	Percent adoption of Bollgard cotton by each county (*i*) at prior time (*t-1*)	
	$Y_{i,t-1}^{\tilde{RR}}$	Percent adoption of Roundup Ready cotton by each county (*i*) at prior time (*t-1*)	

[31] Lagged endogenous explanatory variables are used in each diffusion model in two aspects: learning by doing from the exact technology and learning by doing from other similar technologies. Only one lagged dependent variable is considered as the proxy of learning by doing from exact technology while two separated lagged endogenous explanatory variables are considered as proxies of learning by doing from similar technologies. The superscript ~ is just to emphasize that these variables are considered as learning from similar technologies although in diffusion model specification they are simply lagged endogenous explanatory variable that are also used as the lagged dependent variable in other diffusion model.

Variable		Definition	Proxy
	$\tilde{Y}^{ST}_{i,t-1}$	Percent adoption of Stacked cotton by each county (i) at prior time ($t-1$)	
$Y^{j,j_3}_{i,t}$	$j \neq j_3$	Percent adoption of each biotech cotton and Min.Tillage (j) by each county (i) at time t ($Y^{j,j_3}_{i,t}$ =endogenous independent variables)	Multiple simultaneous effects
$H_0 : a^{j,j_3}_3 \geq 0$	$j \neq j_3$ $j_{3 \neq MinTL}$	Percent adoption of Bollgard cotton by each county (i) at time t in Bollgard model	
$H_0 : a^{j,j_3}_3 \geq 0$	$j \neq j_3$	Percent adoption of Roundup Ready cotton by each county (i) at time t in RR model	
$H_0 : a^{j,j_3}_3 \geq 0$	$j \neq j_3$	Percent adoption of Stacked cotton by each county (i) at time t in ST model	
$H_0 : a^{j,j_3}_3 \leq 0$	$j \neq j_3$ $j_{3 \neq BG}$	Percent adoption of Min. tillage by each county (i) at time t in Min.TL model	
$X^{j,k_4}_{4,i,t}$ $H_0 : a^{j,k_4}_4 \leq 0$		Percent irrigated acres of farm in county i in year t (Irrigated acres$_{i,t}$ / total planted cotton acres$_{i,t}$)	Synergy with other agronomic practice as irrigated land (when appeared on RHS)
$X^{j,k_5}_{5,i}$	$k_5 = 1,2$	Average size of farm in county i ('000 acres) : Avg. of 1997 and 2000 county data (Individual variations regardless of time)	Heterogeneity toward economies of scale
$H_0 : a^{j,k_5}_5 = 0$	$X^{j,k_5=1}_{5,i}$	Size$_i$ = Harvest farm$_i$ / harvest acres$_i$	
	$X^{j,k_5=2}_{5,i}$	Size square$_i$ = size$_i^2$	
$X^{j,k_6}_{6,t}$		Binary dummy variable: Time variations regardless of county level	Time effect
	$X^{j,k_6=1}_{6,t}$	dummy variable when 1997=1; else =0	
	$X^{j,k_6=2}_{6,t}$	dummy variable when 1998=1; else =0	
	$X^{j,k_6=3}_{6,t}$	dummy variable when 1999=1; else =0	

Variable		Definition	Proxy
	$X_{6,t}^{j,k_6=4}$	dummy variable when 2000=1; else =0	
$X_{7,i_s,t}^{j,k_7}$	$j \neq MinTL$	Average pest pressure by state in year *t*	Pest pressure by state
$H_0 : a_7^{j,k_7} \leq 0$	$X_{7,i_s,t}^{j,k_7=1}$	Avg. percent Bollworm infected acres by state in year *t*	Insect pressure by state
	$X_{7,i_s,t}^{j,k_7=2}$	Avg. Weed dollar lost by state in year *t*	Weed pressure by state
$X_{8,i,t}^{j,k_8}$	$j \neq MinTL$	Geographic proximity effect: distances and concentrations of sources of information	Geographic effect through sources of information
$H_0 : a_8^{j,k_8=1} \geq 0$	$X_{8,i,t}^{BG,k_8=1}$	Minimum distances (in miles) from sources of information (25% BG adoption)	Nearness (distance) Effect from sources of adoption info.
$H_0 : a_8^{j,k_8=1} \geq 0$	$X_{8,i,t}^{RR,k_8=1}$	Minimum distances (in miles) from sources of information (25% RR adoption)	
$H_0 : a_8^{j,k_8=1} \geq 0$	$X_{8,i,t}^{ST,k_8=1}$	Minimum distances (in miles) from sources of information (25% ST adoption)	
$H_0 : a_8^{j,k_8=2} \leq 0$	$X_{8,i,t}^{BG,k_8=2}$	Numbers of other BG adoption counties as sources within boundary of AVG. distances of all sources	Area concentration (# of sources) of exact biotech adoption
$H_0 : a_8^{j,k_8=2} \leq 0$	$X_{8,i,t}^{RR,k_8=2}$	Numbers of other RR adoption counties as sources within boundary of AVG. distances of all sources	
$H_0 : a_8^{j,k_8=2} \leq 0$	$X_{8,i,t}^{ST,k_8=2}$	Numbers of other ST adoption counties as sources within boundary of AVG. distances of all sources	
Restrictions in Minimum Tillage model:		$a_2^j, a_7^j.a_8^j = 0$	

Expected Sign of Coefficient Estimates and Hypotheses

- Learning mechanisms
  - Learning by doing from exact technology

: $H_0 : a_1^j \leq 0$

$H_1 : a_1^j > 0$

  - Learning by doing from similar technologies

: $H_0 : a_2^{\tilde{j}} \leq 0 \qquad (j \neq \tilde{j})$

$H_1 : a_2^{\tilde{j}} > 0 \qquad (j \neq \tilde{j})$

- Technology Interdependencies and Complement
  - BG model

: $H_0 : a_3^{j,j_3} \geq 0 \qquad (j \neq j_3 \,\&\, j_3 \neq MinTL)$

$H_1 : a_3^{j,j_3} < 0 \qquad (j \neq j_3 \,\&\, j_3 \neq MinTL)$

  - RR and ST models

: $H_0 : a_3^{j,j_3} \geq 0 \qquad (j \neq j_3)$

$H_1 : a_3^{j,j_3} < 0 \qquad (j \neq j_3)$

  - Minimum tillage model

: $H_0 : a_3^{j,j_3} \leq 0 \qquad (j \neq j_3 \,\&\, j_3 \neq BG)$

$H_1 : a_3^{j,j_3} > 0 \qquad (j \neq j_3 \,\&\, j_3 \neq BG)$

For instance, the hypothesis that RR and/or ST technologies encourage adoption of minimum tillage in the same area can be empirically assessed by evaluating the statistical significance of $a_3^{RR,MinTL}$ and $a_3^{ST,MinTL}$.

- Synergy with other agronomic practices-- irrigation

  $: H_0 : a_4^{j,k_4} \leq 0$

  $H_1 : a_4^{j,k_4} > 0$

  Irrigated land is hypothesized to encourage the adoptions of biotech cotton as well as minimum tillage in the same area.

- Scale effects

  $: H_0 : a_5^{j,k_5} = 0$

  $H_1 : a_5^{j,k_5} \neq 0$

- Time effect
- Pest pressure

  $: H_0 : a_7^{j,k_7} \leq 0$

  $H_0 : a_7^{j,k_7} > 0$

- Geographic proximity as sources of information regarding the adoption of biotech cotton

It is hypothesized that the closer the area of analysis is to the source of information, the more information is shared and the larger the adoption rate. If the unit of analysis is itself the source of information, the distances are to be zero.

$: H_0 : a_8^{j,k_8=1} \geq 0 \qquad (j \neq MinTL)$

$H_1 : a_8^{j,k_8=1} < 0 \qquad (j \neq MinTL)$

It is similarly hypothesized that the more sources of information within the boundary, the more information flows, and the larger the adoption rate.

$$: H_0 : a_8^{j,k_8=2} \leq 0 \qquad (j \neq MinTL)$$

$$H_1 : a_8^{j,k_8=2} > 0 \qquad (j \neq MinTL)$$

Data

Data was obtained from the trait supplier for the purpose of this research. The original data consisted of all the biotech cotton seed transactions (in bags) within the U.S. from 1996 to 2000. In this five year period, there were more than 25,000 cotton growers in 720 counties around the US making at least one purchase of biotech seeds. The biotech cotton seed varieties were comprised of Bollgard© (BG), Roundup Ready©(RR), and (Stacked) Bollgard Roundup Ready©(ST). The purchases of seed were converted into estimated planting acres. Only the numbers of acres and the county of purchase are examined in this analysis. As suggested earlier, the data is aggregated to the county level[32].

Other sources of data were also employed in the model, including data from the Conservation Technology Information Center (CTIC) for county level of tillage acres by year, National Agricultural Statistics Services (NASS) for county level of cotton planted and irrigated acres by year, state level information on cotton insect losses in acres by year

[32] It is assumed that the seed was used at the same year where it was sold.

(Williams, Mississippi State University), and state level dollar losses from weed infestation (Byrd, Mississippi State University). [33]

Geographic proximity:

The two geographic proximity variables attempt to verify whether the source of information matters. The underlying concept is that information diffuses through proximate regions. This is an empirical concept that has not been used in any previous studies. The formulation of this concept into relevant proxies of minimum distance from the source of information and the nearby sources of information is explained below.

The distances among various counties are the same for every time period, while the percent of adoption varies annually. So at a given time, some areas (counties) influence, or are influenced by other counties. The areas (counties) that initially have a certain percent of adoption are considered "sources of information." Deriving the qualification threshold for the "sources of information" is difficult since there are no priors suggested by the literature, particularly for agricultural biotechnology products. For this study, I arbitrarily set the threshold at 25% adoption. The 25% adoption threshold in 1996 implied that about 10% of all the counties were "sources of information." For consistency, previous-year 25% adoption of each biotech cotton variety is used for all three varieties and for all years from 1996 to 2000. Hence, for 1996, there would be no sources of information, since the insect resistant variety was introduced to the market in 1996 and the herbicide tolerant varieties were introduced in 1997.

Having the sources of information is only part of the calculation. The distances between the county of interest and other counties need to be taken into account. Using

[33] Other data comes from Census Bureau for demographic data and various sources to derive the number of dealers by county. These two data sets, however, are not included in the final model.

longitudinal and latitudinal coordinates of county centroids, the distances (in miles) between each of the 781 cotton growing counties can be obtained. Once, the 781X 781 matrix of distances of cotton growing counties is calculated, then the sources of information can be overlaid so that the minimum distances between the county of interest and the sources of information can be derived for use as a proxy of minimum distances from the source of information. It is possible that there could be a number of counties that qualify as sources of information are located nearby each other. With the only proxy of minimum distances between county of interest and the sources of information, only one source of information, the one that yields the minimum distances, is counted.

To take into account other nearby sources of information, all the sources of information within a specified radius are taken into account regardless of their distance to the county of interest. Then, the average distances of all the sources of information are calculated. Lastly, only the sources of information located within the radius of *average* distances are counted and used as a proxy of "numbers of sources of information."

Table 7: Empirical results of BG diffusion model

GM Cotton diffusion Model	**Bollgard® model (BG)**			
Proxy and meaning of explanatory variables	Parameter Estimated	Std. Error	t-Value	Pr > |t|
Dependent variable: %BG_t per county (*t=1996,…,2000*)				
Intercept_BT	4.578	1.307	3.500	0.001
Learning mechanisms				
Learning by doing of exact technology	0.591	0.049	12.190	<.0001
Learning by doing of similar technologies				
Learning from last year RR	0.114	0.021	5.370	<.0001
Learning from last year ST	-0.005	0.029	-0.160	0.876
Learning from others				
Geographic Effect through sources of info.				
Closet to the source of info.BG_t-1 (miles)	-0.012	0.003	-4.430	<.0001
# of Counties within the Means boundary	-0.055	0.018	-3.010	0.003
Multiple simultaneous effects				
With RR adoption	-0.288	0.053	-5.460	<.0001
With ST adoption	-0.038	0.079	-0.480	0.628
Synergies with other agronomic practices				
Synergies with irrigation	0.080	0.018	4.480	<.0001
Heterogeneity toward economies of scale				
Scale bias	0.010	0.004	2.390	0.017
Scale bias squared	0.000	0.000	-1.520	0.129
Time period effect				
dummy variable when 1997 = 1; else = 0	-0.537	1.714	-0.310	0.754
dummy variable when 1998 = 1; else = 0	-0.438	1.865	-0.230	0.814
dummy variable when 1999 = 1; else = 0	-2.931	1.663	-1.760	0.078
dummy variable when 2000 = 1; else = 0	-1.554	1.706	-0.910	0.362
Pest Control Effect				
% Bollworm Infected Acres	0.041	0.009	4.410	<.0001

Table 8: Empirical results of RR diffusion model

GM Cotton diffusion Model	**Roundup Ready® model (RR)**			
Proxy and meaning of explanatory variables	Parameter Estimated	Std. Error	t-Value	Pr > |t|
Dependent variable: %RR$_t$ per county (*t=1996,…,2000*)				
Intercept_RR	-0.092	1.508	-0.060	0.952
Learning mechanisms				
Learning by doing of exact technology	0.507	0.070	7.200	<.0001
Learning by doing of similar technologies				
Learning from last year BG	0.250	0.052	4.790	<.0001
Learning from last year ST	0.102	0.048	2.130	0.033
Learning from others				
Geographic Effect through sources of info.				
Closet to the source of info.RR_t-1 (miles)	-0.031	0.005	-6.290	<.0001
# of Counties within the Means boundary	-0.031	0.032	-0.980	0.327
Multiple simultaneous effects				
With BG adoption	-0.381	0.095	-4.020	<.0001
With ST adoption	-0.117	0.111	-1.050	0.292
Synergies with other agronomic practices				
Synergies with minimum tillage program	0.079	0.024	3.260	0.001
Synergies with irrigation	0.072	0.019	3.700	0.000
Heterogeneity toward economies of scale				
Scale bias	0.001	0.005	0.170	0.864
Scale bias squared	0.000	0.000	-0.120	0.906
Time period effect				
dummy variable when 1997 = 1; else = 0	1.510	0.779	1.940	0.053
dummy variable when 1998 = 1; else = 0	10.862	1.490	7.290	<.0001
dummy variable when 1999 = 1; else = 0	6.075	2.140	2.840	0.005
dummy variable when 2000 = 1; else = 0	10.786	2.756	3.910	<.0001
Pest Control Effect				
Weed lost in dollar	0.006	0.001	5.420	<.0001

Table 9: Empirical results of ST diffusion model

GM Cotton diffusion Model	Bollgard® Roundup Ready® model (ST)			
Proxy and meaning of explanatory variables	Parameter Estimated	Std. Error	t-Value	Pr > |t|
Dependent variable: %ST_t per county (*t=1996,…,2000*)				
Intercept_St	-4.455	1.359	-3.280	0.001
Learning mechanisms				
Learning by doing of exact technology	0.532	0.070	7.550	<.0001
Learning by doing of similar technologies				
Learning from last year BG	0.519	0.088	5.870	<.0001
Learning from last year RR	0.207	0.050	4.160	<.0001
Learning from others				
Geographic Effect through sources of info.				
Closet to the source of info.ST_t-1 (miles)	-0.009	0.002	-3.810	0.000
# of Counties within the Means boundary	0.113	0.063	1.790	0.073
Multiple simultaneous effects				
With BG adoption	-0.617	0.161	-3.840	0.000
With RR adoption	-0.235	0.122	-1.920	0.054
Synergies with other agronomic practices				
Synergies with minimum tillage program	0.088	0.027	3.200	0.001
Synergies with irrigation	0.040	0.019	2.060	0.040
Heterogeneity toward economies of scale				
Scale bias	0.013	0.005	2.720	0.007
Scale bias squared	0.000	0.000	-1.620	0.106
Time period effect				
dummy variable when 1997 = 1; else = 0	-4.713	0.888	-5.310	<.0001
dummy variable when 1998 = 1; else = 0	0.650	1.086	0.600	0.550
dummy variable when 1999 = 1; else = 0	-1.753	2.416	-0.730	0.468
dummy variable when 2000 = 1; else = 0	4.298	2.753	1.560	0.119
Pest Control Effect				
% Bollworm Infected Acres	0.058	0.012	4.860	<.0001
Weed lost in dollar	0.004	0.001	2.850	0.004

Table 10: Empirical results of minimum tillage diffusion model

GM Cotton diffusion Model	**Minimum Tillage Practices**			
Proxy and meaning of explanatory variables	Parameter Estimated	Std. Error	t-Value	Pr > |t|
Dependent variable: %Min.TL$_t$ per county (*t=1996,…,2000)*				
Intercept_MinTL	10.631	2.463	4.320	<.0001
Learning mechanisms				
Learning by doing of exact technologies	0.409	0.027	15.060	<.0001
Multiple effect & Synergies with GM varieties				
Synergies with RR varieties	0.166	0.050	3.360	0.001
Synergies with ST varieties	0.359	0.054	6.650	<.0001
Synergies with RR and/or ST irrigation	0.095	0.026	3.610	0.000
Heterogeneity toward economies of scale				
Scale bias	-0.006	0.010	-0.670	0.506
Scale bias squared	0.000	0.000	1.090	0.276
Time period effect				
dummy variable when 1997 = 1; else = 0	-2.294	1.277	-1.800	0.072
dummy variable when 1998 = 1; else = 0	-3.683	1.352	-2.730	0.007
dummy variable when 1999 = 1; else = 0	-8.318	1.450	-5.740	<.0001
dummy variable when 2000 = 1; else = 0	-11.048	1.706	-6.480	<.0001

Empirical Results

Similar to the individual adoption findings, diffusion is influenced by the level of diffusion of biotech cotton varieties in the previous year, synergies with agronomic practices, and by the economics of the new technologies. Lagged biotech cotton adoption allows for "learning by doing" from either the exact technology or similar technologies within the limits of a county.

Learning from others (neighbors) in aggregate adoption is redefined and utilized both in the "information nearness" and "information concentration" proxies. This approach takes into account the closest distance to the only designated source location (as information nearness) and the concentration level of all designated sources within a certain boundary (information concentration). Information nearness is statistically significant across all technologies while information concentration seems to matter only in the ST model.

Learning by doing of exact technologies is the most influential factor in all but the ST models. Multiple simultaneous effects (substitutability for biotech cotton models and complementarities with minimum tillage model) are also dominant factors. Substitutability to BG in ST model is the strongest factor. Due to the fact that ST was first introduced on the market in 1998, the diffusion of ST was still in the early stage in 2000, which is the latest data available in this study. This fact may contribute to some behavior that is unexpected or incongruent to the stated hypotheses.

Diffusion of biotech cotton varieties in period $t+1$ increases, on average, by more than 50% for every 100% increase in the acreage of the exact same technology in period t with all other factors held constant. Diffusion is also influenced by use and learning from similar technologies. For instance, BG diffusion also relies on previous RR aggregate adoption in the same county. On average BG diffusion increases by about 10% for every 100% increase in previous aggregate RR adoption at the same county with all other factors held constant. In the RR case, RR diffusion increases by about 10% (and up to 25%) for every 100% increase in previous ST adoption (or previous BG at the same county with all other factors held fixed). As for the ST diffusion model, approximately

50% of the increases in ST diffusion come from an 100% increase in either previous RR or BG with all other factors held constant.

The diffusion model also indicates that learning from others has a strong proximity character and affects diffusion. The closer to the source of information a county is, the more likely is that diffusion of the exact technology in that county will increase. For example, in BG model, current BG diffusion increases about 1.2% for every 100 miles closer to the nearest BG source of information is. In the RR model, any county with at least 25% adoption of RR in period *t+1* is responsible for a 3% increase in period t RR diffusion within the 100 miles radius if the particular county is the closet source of information to any other counties. In the ST model, current ST diffusion increases almost 1% for every 100 miles in radius closer to the nearest source of ST information a year earlier.

Information concentration captures all the surrounding sources of information. All the sources of information surrounding a particular county are designated and their distance to the second county is added. The average distances to all the sources are calculated, but only the numbers of sources within the average distance are counted toward information concentration. Those counties that are located outside the average distances are considered too remote and consequently ignored. Only the past ST concentrations influence the current ST diffusion. Given the early stages of ST diffusion, it is possible that such effect is spurious.

Substitutability is found to have a strong impact on aggregate adoption, particularly, in RR and ST diffusion models. As BG lost popularity after 1998, both RR and ST would appear to have substituted for BG. The empirical results suggest that the current BG diffusion decreases on average 29% for every 100% increase in current RR aggregate adoption. Reverse effects also exist suggesting that, on average, 38% decreasing in RR diffusion when BG increases by 100%. Clearly, although BG and RR control different types of pests, they seem to act as substitutes as they do compete for limited land.

The empirical model also indicates that the current ST diffusion increases by 62% for every 100% decrease in current BG aggregate adoption. This finding suggests that the introduction of a new technology can affect the adoption level of an old one to the point of disadoption. The large marginal effects suggest that ST directly displaces BG much more that RR would. This is reasonable due to the similar properties of BG and ST. The current ST diffusion also increases by about 20% for every 100% decrease in current RR.

The strong synergy between minimum tillage and herbicide-tolerant varieties is once again confirmed in the diffusion model. Minimum tillage is one of the factors responsible for a substantial level of diffusion of herbicide tolerant cotton. For every 100% increase in current minimum tillage practice, diffusion of herbicide-tolerant cotton would increase from 3% to 8% with other factors held constant. The reverse impact is significantly stronger. Herbicide-tolerant cotton diffusion strongly encourages the diffusion of minimum tillage practice. The minimum tillage practice increases 36% for every 100% increase in ST cotton. Similarly, minimum tillage practices increase 17% for every 100% increase in RR cotton. From this finding, it is clear that minimum tillage diffusion relies proportionally on the concentration of herbicide tolerant-cotton.

In addition to the synergy between herbicide tolerant cotton and minimum tillage, synergies also exist between biotech cotton and irrigated acreage. Irrigated acres are statistically significant at 1% and encourage diffusion of all biotech and minimum tillage practices. For every 100% increase in currently irrigated land, diffusion of biotech cotton as well as minimum tillage practice would increase by 4% to 10%.

Economics have a significant impact on the diffusion of all biotech cotton varieties. The percentage of bollworm infected acres and dollar losses due to weed infestation were used as proxies of pest pressure and economic need for improved methods of pest control. All biotech cotton diffusion increased as pest pressure rises. In the BG model BG diffusion increased 4% for every additional 100 bollworm infected acres in the area. In the RR model, RR diffusion increased 6% for every additional $1,000,000 lost to weed damage in the area.

Average size of farms and their quadratic effect are used as proxies of scale bias. Only BG diffusion showed any significant scale effects and even then such impact was rather small in value. Specifically, BG diffusion increased by 10% for every 1,000 acres increase in the average farm size in the particular county. Given that BG diffusion has been shrinking, the result may be due to the fact that larger farms have been slower to disadopt.

In all, much like with the adoption model in chapter 4, the stated hypotheses are supported within the context of the diffusion model

CHAPTER 6

SUMMARY AND CONCLUSIONS

In this study I proposed the following hypotheses: (a) US cotton producers adopt biotechnologies in order to maximize an expected stream of profits over a given period of time. Accordingly, producer adoption decisions are closely influenced by perceived economic gains from various biotechnologies. (b) US cotton producers account for interdependencies and choose bundles of conventional technologies, agricultural biotechnologies and relevant agronomic practices. Hence, their behavior is characterized by multiple simultaneous and interdependent adoption decisions. (c) In the presence of complexity and uncertain performance, US cotton producers use multiple learning mechanisms to optimize the use of the three cotton biotechnologies over time. They partially adopt one or more of the technologies and learn by doing. They also learn by observing other users. Hence, their adoption decisions are dynamic in nature. (d) Cotton biotechnologies are highly divisible and require no significant upfront investment. Their adoption implies no scale bias and it is evenly distributed across all firm sizes. (e) Dynamic and simultaneous considerations explain not only adoption decisions among producers in any given year but also aggregate diffusion patterns observed over a period of time.

I empirically tested these hypotheses within the context of two closely linked but separate adoption and diffusion models for three selected cotton biotechnologies. For the adoption model, I used detailed survey data for a representative sample of US producers to examine the influence of the following factors: perceived innovation rents, perceived innovation risk, technology interdependencies, learning from past adoption decisions, adoption of related agronomic practices, and farm size. For the diffusion model, I examined the influence of similar variables on the behavior of the whole population of adopters over multiple years.

The population of the potential adopters is not considered homogeneous. Farms are assumed to differ in their characteristics (e.g. size, agronomic practices, and use of other technologies like irrigation). Farm location can also point to other significant differences among farms that can influence their behavior towards innovation (e.g. differential pest pressures). Farm heterogeneity is assumed to explain, in part, differential adoption and diffusion levels in cotton biotechnologies.

In their effort to maximize expected profits and minimize risks, cotton producers may partially adopt one or more new biotechnologies. These new technologies compete for land in any given period, and served as sources of basic knowledge for further adoption in following periods. I model this producer behavior within the framework of an optimal control problem.

While the derivations presented here are cumbersome and not elegant, some interesting observations can be made about the results. First, depending on the efficiency of the learning processes, the new technologies can replace the traditional one. Second, the relative learning of each new technology affects their individual and aggregate adoption. Third, depending on the relative efficiency of each learning process, it is possible to reverse the adoption of one of the new technologies, in favor of increasing the adoption of another. Hence, depreciation of a new technology can happen through own and cross learning and through advancement of the alternative new technology. These results would be counter-intuitive without considering the adoption of the two new technologies jointly and their cross-learning effects.

The most significant insight obtained through the theoretical developments in this study, however, is an indirect one. Derivations demonstrated that as one attempts to add relevancy to theoretical constructs of producer adoption decisions and account for technology interdependencies, learning and other relevant effects, the complexity of the theoretical derivations increases and solutions become quickly intractable. This result suggests that empirical analysis is all that much more important, or may be the only way to examine relevant complexity in innovation adoption and diffusion.

For these reasons, the empirical analyses of adoption and diffusion patterns were ultimately the focus of this study. Both the survey and population data suffered from heteroscedasticity and in the case of the diffusion data, also from serially correlation. Thus, parameters were estimated through Generalized Method of Moments which yield consistent and efficient estimates.

Empirical results confirmed the stated hypotheses. They showed: that adoption is driven by various learning mechanisms and perceptions of innovation rents and risk. All biotechnologies substitute one another and compete for land. Synergies between biotech cotton and other agronomic practices, including minimum tillage and irrigation, are strong. This is especially true in the case of herbicide-tolerant varieties and minimum tillage practices.

The dynamic interdependencies among the three biotechnologies over multiple periods were intensity. For example, in any period, all varieties compete for land.

However, previous experience with any of the new varieties encourages further adoption not only its own trait but of similar traits as well. There are strong synergies between herbicide tolerant and minimum tillage practices at any given period that lead to reinforceable adoption relationships. This finding confirms the hypothesis that has been posed but not quantified in previous literature that herbicide tolerant biotech varieties contribute to the adoption of reduced tillage practices with associated gains in soil conservation.

The empirical results indicated that there is generally no scale bias in the adoption of biotechnologies, but when there is, herbicide resistant biotech cotton is adopted more by smaller firms. Perceived economic benefits and technology effectiveness were found to have a key positive impact on adoption.

The empirical results of this study therefore tell a story of a complex adoption decision process where farmers consider interdependent technologies with strong substitutability but also synergistic relationships with other agronomic practices; where complex learning mechanisms are utilized to improve innovation pay offs; and where complex perceptions of innovation gains—both pecuniary and non-pecuniary—are considered. These complexities in adoption decisions have not been uncovered or investigated in prior adoption studies of agricultural innovations.

The empirical results from the diffusion models were also consistent with those of the adoption models. Empirical results showed that diffusion in any given year is influenced by the level of diffusion in the previous year, synergies with agronomic practices, and by the economic payoffs of the new technologies. Substitutability among new technologies was found to have a strong impact on diffusion, particularly, in herbicide resistant and stacked cotton biotechnologies. Learning by doing and from others were also found to influence the diffusion levels of biotech innovations.

In the diffusion model, learning from others (neighbors) was measured through "information nearness" and "information concentration" proxies. This approach took into account the closest distance to an information source and the concentration level of information sources within a certain boundary. Information nearness was found to be statistically significant across all technologies while information concentration seemed to matter only in the stacked model.

Learning by doing of exact technologies was found to have a significant impact on diffusion. Diffusion was also influenced by use and learning from similar technologies.

Substitutability among the three new technologies was found to have a strong impact on diffusion, particularly, in the herbicide resistant and stacked diffusion models. Clearly, although the three cotton biotechnologies control different types of pests, they act as substitutes as they do compete for limited land.

The strong synergy between minimum tillage and herbicide-tolerant varieties is once again confirmed. Minimum tillage use is one of the factors that is responsible for a substantial level of the diffusion of herbicide tolerant cotton. The opposite is also true. From this finding, it is clear that minimum tillage diffusion relies on the adoption and diffusion of herbicide tolerant-cotton as well. Synergies also exist between biotech cotton and irrigated acreage.

Innovation rents have a significant impact on the diffusion of all biotech cotton varieties. The percentage of bollworm infected acres and dollar losses due to weed infestation were used as proxies of pest pressure and economic need for improved methods of pest control. All biotech cotton diffusion increased as pest pressure grew.

Only the diffusion of insect resistant biotech cotton showed any significant scale effects and even then such impacts were rather small in value. Given that the diffusion of insect resistant cotton has been shrinking, the result may be due to the fact that larger farms have been slower to disadopt. In all, much like with the empirical results of the adoption model, the stated hypotheses were supported within the context of the diffusion model

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VITA

Pasu Suntornpithug was born Deember 17, 1969 in Bangkok, Thailand. He followed his parent who both are teachers at the time and worked for department of teaching education, and attended elementary school I and element school II in Nakorn Rachasrima and Ayuthaya , respectively. After attending Triam Udom Suksa, the reputable public schools in Bangkok, he received the following degrees: B.S. in Agricultural Economics from Kasetsart University, Thailand (1993); M.S. in Agricultural Economics from the University of Missouri-Columbia (1997); Ph.D. in Agricultural Economics from the University of Missouri-Columbia (2004). He is married to the former Nichaya Sukpanich of Bangkok, Thailand, and he is proudly a father of Saranya Grace Suntornpithug.