

**TECHNOLOGY ADOPTION: WHO IS LIKELY TO ADOPT AND HOW DOES
THE TIMING AFFECT THE BENEFITS?**

A Dissertation

by

DEBRA RUBAS

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

August 2004

Major Subject: Agricultural Economics

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ABSTRACT

Technology Adoption: Who Is Likely to Adopt and How Does the Timing Affect the Benefits? (August 2004)

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Many fields of economics point to technology as the primary vehicle for change.

Agencies pushing change often promote technology adoption to achieve their goals. To improve our understanding of how efforts to push new technologies should be focused, two studies are undertaken. The first study defines and tests for universality using meta-regression analysis on 170 analyses of agricultural production technologies. The second study, a case study on an emerging information technology – climate forecasts, examines how the timing of adoption affects the benefits.

A factor exhibiting a systematic positive or negative effect on technology adoption is a universal factor. If the impact is the same regardless of location or technology type, the factor is strongly universal. The factor is weakly universal if the impact varies by location or technology type. Education and farm size are found to be weakly positive universal, age is found to be weakly negative universal, and outreach is not found to be a universal factor in the adoption of technology. These results indicate that technology-promoters may want to change their approach and focus on younger, more educated producers with larger farms.

In the second study, an international wheat trade model incorporating climate variability is used to simulate different scenarios when wheat producers in the U.S.,

Canada, and Australia adopt ENSO-based forecasts for use in production decisions.

Adoption timing and levels are varied across countries in the different scenarios. The results are highly consistent. Early adopters benefit the most, there is no incentive for more producers to adopt after 60% to 95% have adopted (meaning the adoption ceiling has been reached), and slower adoption corresponds to ceilings closer to 60% than 95%.

Examining technology adoption from two angles provides a deeper understanding of the adoption process and aids technology-promoters in achieving their goals. In addition to focusing on younger, more educated producers with larger farms, technology-promoters wanting wide-spread adoption with high benefits need to push constituents to adopt early and fast.

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CHAPTER I

INTRODUCTION

Technology plays a vital role in many fields of economics. Environmental economists are concerned with how new technologies affect the environment (Tietenberg). Natural resource economists are interested in new technologies that improve the efficiency with which nonrenewable resources are used (Tietenberg). Many macroeconomists point to technological change as the primary impetus for economic growth (Romer).

Development economists, also interested in economic growth, often push projects involving technology transfers from wealthy areas to poor areas (Feder, Just, and Zilberman). And the list continues.

The availability of new technologies does not, however, automatically lead to a cleaner environment, more efficient use of resources, economic growth, or development. Technologies must be adopted, which occurs only when they add value to the individuals, firms, industries, and nations who adopt them. To understand the role of technology, it is important to understand the adoption process. Understanding the factors that affect adoption and knowing how benefits are likely to be distributed allows technology-promoters to target their programs.

Hundreds of studies have examined factors associated with the adoption of a specific technology in a specific area. For those pushing technology adoption, the narrowness of these studies makes extrapolation difficult. Meanwhile, the conflicting

This dissertation follows the style and format of the *American Journal of Agricultural Economics*.

results of such varied studies make generalizations nearly impossible. In addition to understanding what factors lead to technology adoption, it is important for technology-promoters to be able to predict who will benefit from adoption. Previous studies have examined benefits to adoption *ex post*, after they have already taken place, or they have predicted benefits *ex ante* under unrealistic scenarios. Studies on the adoption of climate forecasts, for example, have predicted how society will benefit if all agricultural producers simultaneously adopt them. The literature on technology adoption, however, indicates that adoption takes place over time and generally stops before everyone has adopted. Assuming simultaneous adoption by all agents may bias estimates of the benefits.

Objectives

The overall objective of this dissertation is to improve our understanding of how efforts to push new technologies can be focused to increase society's welfare by adoption of appropriate technology. This overall objective is met by accomplishing two specific subobjectives. The first subobjective is to improve our understanding of what factors are important in determining whether an agricultural producer is likely to adopt a new technology. Illustrating how the timing of technology adoption affects agricultural producers' benefits from adopting is the second subobjective.

The first subobjective is addressed through a meta-regression analysis of previous studies that empirically examine the adoption of a production technology in agriculture. Factors that systematically lead to adoption regardless of location or type of technology are said to be universal. A test for universality is developed and applied to

four factors for which previous studies have reported mixed results. The test determines whether a factor is universal, and if so, the direction (positive / negative) and strength (strong / weak) of universality. The meta-regression analysis also indicates how a study's methodology may influence the apparent relation between producer attributes and technology adoption. The test for universality is general enough to be applied to other settings. For example, one could examine factors believed to increase an individual's willingness-to-pay for environmental quality. Understanding how factors leading to adoption vary by location and type of technology may help technology-promoters know who to target in diverse settings.

The second subobjective is met through a case study that illustrates how the timing of technology adoption affects the distribution of adoption benefits. An emerging information technology, seasonal climate forecasts, is examined. Though most people tend to think of new technology as something physical, many new technologies are information. The decision to use a new piece of production equipment and the decision to use new information to alter one's production process are similar. A model of the international wheat market is used to examine various scenarios of producers in different countries adopting seasonal climate forecasts. Results illustrate how the distribution of benefits may change when the timing of adoption changes. Combining the knowledge of who is most likely to adopt with an understanding of how the timing of adoption affects the benefits allows technology promoters to target those most likely to adopt and benefit in a given setting.

Dissertation Structure

The literature on technology adoption and climate forecast use, summarized in Chapter II, provides the context for the two studies that follow. The meta-regression-analysis, which addresses the first subobjective, is the subject of Chapter III. Chapter IV deals with the second subobjective through the case study of seasonal climate forecast adoption. In Chapter V, the findings of the two studies are summarized, overall conclusions are drawn, and areas for further study are proposed.

CHAPTER II

THE LITERATURE ON TECHNOLOGY ADOPTION

Technology adoption has been studied at the firm or household level, the industry level, and the national level. Some studies focus on how adoption spreads. Other studies examine characteristics of technologies that tend to be adopted quickly, while others focus on characteristics of decision makers or firms that relate to early adoption. The scope, approach, and methods have varied widely. Though conflicting results are common, some tendencies have emerged. These tendencies, which cut across different avenues of research, are the focus of this review.

The S-shaped Curve

Perhaps the most consistent result in the technology adoption literature is that the adoption path follows a sigmoid (s-shaped) curve. When first released, only a few agents adopt the technology. Then, for reasons discussed in later sections, more agents adopt, increasing the rate of adoption. As time goes on, the number of potential adopters decreases, causing the rate of adoption to decrease. Eventually, an adoption ceiling is reached. At this point, there is no increase in adoption. In most cases, the ceiling is reached before all agents have adopted. For those who choose not to adopt, the technology may not be profitable, it may not be feasible, or an even newer technology may have been adopted instead. The s-shape has been explained using three main approaches: epidemic, Bayesian learning, and game theory.

Epidemic Approach

The epidemic approach, put forth by Mansfield (1961), contends that as information spreads (much like a disease), firms adopt. Mansfield's (1961 p. 762-763) model is based on the hypothesis that "...the probability that a firm will introduce a new technique is an increasing function of the proportion of firms already using it and the profitability of doing so, but a decreasing function of the size of the investment required." This explanation has been expanded to look at heterogeneous firms and industries. The s-shaped curve is then said to be caused by inter-firm or inter-industry differences (Romeo; Mansfield 1973). Factors such as firm size, market concentration, R&D expenditures, and education level of decision makers have been suggested as factors influencing adoption. The key, though, is access to information. If a new technology is known to be profitable or if others are using it, there is a bandwagon effect. Adoption spreads through information.

Bayesian Learning Approach

Criticizing the epidemic approach for its lack of a theoretical basis and exogenously determined adoption ceiling, Stoneman (1981) develops a model based on the Bayesian theory of learning. His model focuses on intra-firm diffusion instead of inter-firm diffusion. The s-shape arises because agents change their intensity of adoption as they learn about the new technology and modify their expectations. Stoneman's (1981) model introduces uncertainty and adjustment costs, absent in Mansfield's (1961) model, and allows the adoption ceiling to be determined endogenously. His results are similar to those of Mansfield, though he feels his model includes "...a much richer menu of

factors that can influence diffusion and is much more closely linked to those parts of economics to which economists are so attached, such as choice theory” (Stoneman 1983 p. 81).

Feder, Just, and Zilberman (p. 275) note, “It is observed that in many cases farmers experiment with new technologies or new practices on a small portion of their land. This suggests that some Bayesian learning processes are taking place.” Tsur, Sternberg, and Hochman extend Stoneman’s model by introducing dynamic factors into the adoption decision of divisible technologies. They consider two types of learning. First, there is learning by doing, in which one gains information by using the new technology. The other type of learning “...consists of collecting and processing information. It determines how perceptions about the performance of the innovation are updated and takes on the form of Bayesian learning” (Tsur, Sternberg, and Hochman p. 353). Their results are discussed below in the section on risk.

Stoneman (1983) compares the epidemic approach to more modern theoretical models of diffusion, where very little, if any, account is taken of information spreading or other epidemic-type forces. According to these modern theories, the date at which a firm adopts depends on its rank, stock, and order effects. These effects determine the diffusion path, which again has an s-shape.

Rank effects have to do with differing characteristics of firms resulting in different rates of return from adopting a new technology. There are acquisition costs, which decrease over time. Firms adopt when the benefits of adoption exceed the costs. Therefore, firms with the greatest net returns adopt first, followed by those with the next

greatest and so on. Stock effects, "...result from the assumption that the benefit to the marginal adopter from acquisition decreases as the number of previous adopters increases" (Stoneman 1983 p. 504). As more firms adopt, production costs fall, which lead to changes in output and prices. At the same time, the costs of adoption decrease over time, allowing more agents to adopt. This creates the diffusion path. Stoneman (1983) calls this the "game-theoretic" approach, which is discussed in the next section. Order effects "...result from the assumption that the return to a firm from adopting a new technology depends upon its position in the order of adoption, with high-order adopters achieving a greater return than low-order adopters" (Stoneman 1983 p. 504). Decisions by early adopters can, therefore, affect when stragglers adopt.

Stoneman (1983) tests these theories by examining computer numerically controlled machine tool adoption in the United Kingdom. He compares rank, stock, and order effects with the epidemic approach and finds evidence for the existence of rank and epidemic effects (in which he included endogenous learning effects), but not stock or order effects. His findings, therefore, do not support the game theoretic approach discussed below. Most empirical studies, however, follow Mansfield and Stoneman's earlier works. They generally focus on information and manager or firm-specific characteristics (from Mansfield works) and acquisition costs, uncertainty, and learning effects (from Stoneman's works).

A recent thread in the literature uses the term "network externalities" to describe situations when the number of adopters positively or negatively affects the benefits of adoption, which, in turn, positively or negatively affects the number of adopters. For

example, Goolsbee and Klenow found people were more likely to buy their first home computer when those around them owned computers. They believe information spillovers cause increased adoption. Lange, McDade, and Oliva cite several studies finding that when there are competing high-technology products, there tends to be a bandwagon effect. Firms tend to form communities that adopt many of the same products. For example, Windows was chosen over DOS, and VHS was chosen over BETA. Because the presence of network externalities causes one agent's actions to affect the decisions of other agents, strategic behavior can result. Game theory is often used to study this strategic behavior (Haruvy and Prasad; De Bijl and Goyal; Kristiansen).

Game Theory Approach

Strategic behavior is also used to explain the s-shaped adoption curve. Reinganum looks at a two-person, non-zero sum game where players are identical and information is perfect. She finds that two Nash equilibria exist. In each equilibrium, one player adopts first. When firms are not identical and there is a net gain for the first adopter, there is always an asymmetric Nash equilibrium. Reinganum examines the case of many firms and finds that as long as the value of adoption declines with the number of adopters, firms adopt sequentially. This is true even when the firms are identical and information is perfect. Her results provide evidence for the existence of a diffusion process. The s-shape is shown by Jovanovic and Lach to be the result of learning by doing and competition. They assume potential adopters are identical and have perfect foresight. Learning by doing results in lower costs for later entrants, but waiting also means facing

lower output prices with older technology. They show that initially the diffusion path is convex because learning by doing effects are decreasing. Eventually, the path will be concave as the adoption ceiling is approached. This ceiling is determined endogenously.

Empirical Studies

Empirical studies support the s-shaped adoption pattern over time. A number of studies use the logistic curve to estimate the rate of technological diffusion as a function of industry, firm, or technology characteristics. This work began with Grilches in his seminal study of hybrid corn and was extended by Mansfield (1961 and 1973) and Romeo. Knudson compares a static logistic model to a dynamic logistic model and finds the dynamic model fits the data better. The dynamic model is more flexible regarding symmetry and inflection points, which allows the determinants of diffusion to change over time. Sultan, Farley, and Lehmann do a meta-analysis of 15 studies estimating rates of diffusion for different technologies in diverse industries. They find the estimated diffusion rates vary "...widely with the type of innovation examined, the estimation procedure employed, and the presence of other variables" (Sultan, Farley, and Lehmann p. 75).

Many adoption studies, however, do not have sufficient data to look at adoption over time. These studies use s-shaped curves to examine the probability of adoption at a given point in time. The logistic curve is also used frequently in these cross-sectional studies (Jarvis; Caffey and Kazmierczak, Harper et al.; and Lee and Stewart). Other studies, such as those by Dorfman, Khanna, Lin, and Negatu and Parikh, use the

cumulative normal distribution. There is generally little difference between the two (Polson and Spencer).

Some economists have argued for other forms. Feder and Umali (1993 p. 224-225) explain

The logistic model imposes a symmetric S-shaped diffusion trend which attains a maximum diffusion rate when 50% of the potential cumulative adopters have adopted the innovation...The Gompertz curve imposes an asymmetric (positively skewed) trend; it attains its point of inflection when diffusion has reached approximately 37% of the upper bound...The cumulative log-normal is another member of the exponential growth curves which can reproduce a whole family of asymmetric S-shaped curves, because the inflection point is variable...Bewley and Fiebig criticized the logistic and Gompertz models because of their rigidity. They developed the FLOG [flexible logistic] model whose point of inflection and degree of symmetry are determined by the data set rather than imposed.

The Adoption Decision

Theoretical models point to an s-shaped curve; empirical studies support these models. This shape implies sequential adoption and has led to many hypotheses about who will adopt first. The next three sections focus on the adoption decision, examining characteristics of decision-makers, firms and industries, and technologies that correspond to early adoption. On all three levels, many characteristics have been proposed, and many empirical studies have tested the hypotheses. For some characteristics, the results vary widely. For others, there is more consistency across technologies, industries, and national boundaries.

Socioeconomic Characteristics of Decision Makers

A large body of literature exists that attempts to explain the socioeconomic characteristics of decision-makers that tend to speed adoption. In 1968, after examining studies of technological diffusion from many different fields, Rogers and Stanfield (p. 234) noted, "Diffusion research is thus emerging as a single body of concepts and relationships, even though the investigations are conducted by researchers in many scientific disciplines." In their book, Rogers and Stanfield (p. 229) define "innovativeness" as "...the degree to which an individual is relatively earlier than other members of his social system to adopt new ideas." Using this definition, they list the following generalizations after examining hundreds of empirical studies from 14 different disciplines (Rogers and Stanfield p. 249-250).

1. Education is positively related to innovativeness.
2. Literacy is positively related to innovativeness.
3. Income is positively related to innovativeness.
4. Level of living is positively related to innovativeness.
5. There is no consistent relationship between age and innovativeness.
6. Knowledgeability is positively related to innovativeness.
7. Attitude toward change is positively related to innovativeness.
8. Achievement motivation is positively related to innovativeness.
9. Education aspirations are positively related to innovativeness.
10. There is not yet adequate evidence about the relationship of such attitudinal variables as business orientation, satisfaction with life, empathy, and rigidity, to innovativeness.
11. Cosmopolitanness is positively related to innovativeness.
12. Mass-media exposure is positively related to innovativeness.
13. Contact with change agencies is positively related to innovativeness.
14. Deviancy from norms (of the social system) is positively related to innovativeness.
15. Group participation is positively related to innovativeness.
16. Interpersonal-communication exposure is positively related to innovativeness.

17. Opinion leadership is positively related to innovativeness.
18. Relative advantage of the innovation is positively related to the rate of adoption.
19. Compatibility of the innovation is positively related to rate of adoption.
20. Fulfillment of felt needs by the innovation is positively related to rate of adoption.
21. There is not adequate evidence about the relationship of rate of adoption to complexity, divisibility, communicability, availability and immediacy of benefit from adopting innovations.
22. There is not adequate evidence as to the relationship of various change-agency strategies and the rate of adoption of innovations.

The first 17 generalizations relate primarily to the decision-maker.

Generalizations 18-20 relate to the technology and are discussed in a later section.

Although their paper was written in 1968 and covered disciplines far afield of economics, many (though not all) recent empirical studies by economists support these early findings. For generalizations 21 and 22, there was little to no evidence as of 1968. Recent literature has established evidence for some of these relationships.

Education, experience, and age. Education has been used as a proxy for many attributes including some of Roger and Stanfield's variables such as education, literacy, knowledgeability, and educational aspirations. Nelson and Phelps (p. 69) state, "Education enhances one's ability to receive, decode, and understand information." They go on to hypothesize (p. 70), "Educated people make good innovators, so that education speeds the process of technological diffusion." Lin points out that though imperfect information causes new technologies to be risky, better-educated people are better prepared to manage the risk. Rahm and Huffman (p. 407) add, "Human capital variables [including schooling] may enhance the efficiency of adoption decisions."

In separate empirical studies, all of the above authors found education to relate positively to adoption, as have many others including Khanna in her study of technology adoption in four Midwestern States, Zepeda (1990) in her predictions of bST use by California dairy farmers, and Mansfield (1973) in his study of industry. A number of studies found education not to be significantly related to adoption (Shapiro, Brursen, and Doster; Barham; Dong and Saha; Taylor and Miller), and a few have found it to be negatively related to adoption (Dorfman; Harper et al.; Ascough et al.). Shapiro, Brursen, and Doster, for example, do not find education to be significant in the decision to double-crop soybeans and wheat. Dorfman, on the other hand, finds education to negatively relate to the adoption of new technology by apple-growers in the U.S. Similarly, Harper et al. find education to negatively relate to the adoption of an integrated pest management technology among Texas rice farmers.

Experience is informal education. Variables relating to experience are found in many economic models, with mixed results. Experience may positively relate to technology adoption by increasing a decision maker's ability to assess whether a new technology will be profitable (Khanna). Lin finds experience to relate positively to the adoption of hybrid rice in China. On the other hand, experience may be related to age, which has often been shown to negatively relate to adoption (Saha, Love, and Schwart; Zepeda (1987); Polson and Spencer). Caffey and Kazmierczak, for example, find experience in the aquaculture industry in Louisiana does not relate to the adoption of flow-through and recirculating technology in soft-shell crab production.

A number of studies have included age in their models, and though many, like those listed above, show age to be negatively related to adoption, some show a positive relation. For example, Adesina and Baidu-Forson's study of the adoption of improved rice varieties in Guinea find age to relate positively to adoption, as do Comer et al. in their study of sustainable practices in Tennessee and McNamara et al. in their study of IPM adoption by peanut producers in Georgia. Other studies show no significant relation between adoption and age. Examples include Amponsah's study of computers and information services in North Carolina, Baker's study of computer adoption in New Mexico, and Caviglia and Kahn's study of sustainable agricultural practices in Brazil.

Outside links. Outside links correspond to Roger and Stanfield's characteristics 12, 13, 15, and 16 that relate to early adoption. If adoption spreads like a disease, through contact, the more contact one has with the outside, the more information one will have and the more likely it is that one will adopt. Hooks, Napier, and Carter find contact with a county extension agent to be significantly related to the adoption of high and intermediate technologies. Harper et al. find attendance at field days to be related to the adoption of insect sweep nets in conjunction with treatment thresholds among Texas rice farmers. Polson and Spencer find the level of extension services to be positively related to the adoption of improved cassava in Nigeria. Zepeda (1990) finds industry involvement (membership in three or more industry organizations) to be positively related to the adoption of bST among California dairy farmers. Caffey and Kazmierczak do not find university extension services to relate to improved aquaculture practices in Louisiana. They hypothesize this lack of relationship is because there has been no

contact for a long time. Caffey and Kazmierczak further speculate that if contact is re-established, it may relate to quicker adoption. Feder and Slade examine information acquisition and its role in the adoption decision. So sure are they that increased extension activities speed adoption that they build this into their model as an assumption. On the industry side, Gibbs and Edwards find that ties with the outside technical community relate positively to the adoption of technology in Britain.

On the other hand, a number of studies find no statistical relationship between outside links and adoption. For example, Abd-Ella, Hoiberg, and Warren find the scale of extension contact to be insignificant in the adoption of recommended farm practices in Iowa. Kaliba et al. find extension contact to be insignificant in the adoption of inorganic fertilizer for maize production in western Tanzania, while Neill and Lee find extension to be insignificant in the adoption of cover crops in Honduras. A few other studies find outside links to be negatively related to adoption. Sheilkh, Rehman, and Yates, for example, find the number of visits to an extension agent to be negatively related to the adoption of no-tillage practices in Pakistan. Dimura and Skuras find the number of contacts with organizations in one year to be negatively related to the adoption of new tobacco varieties in Greece.

Risk aversion. Though Rogers and Stanfield do not specifically mention risk, generalizations 7, 8, and 10 deal with attitudes and motivations relating to risk. In recent literature, risk and uncertainty have taken two forms. Agents can be more or less risk averse, and the technology can be more or less risky. Agent risk is discussed here, whereas technology risk is discussed in a later section. One difficulty with including

risk aversion in a model is that it is difficult to measure. In one study, Tsur, Sternberg, and Hochman find that risk aversion positively affects adoption. This is because risk-averse agents do not want to take the risk of not trying the innovation. In examining how farmers decide to mix modern and traditional crop production, Feder (p. 271) finds that "...the optimal allocation of land for the modern crop declines with higher degrees of risk aversion." This has more to do with intensity of adoption than adoption versus nonadoption. Still, Feder's finding somewhat contradicts Tsur, Sternberg, and Hochman's findings.

In another study, Feder and O'Mara (p. 61) find

The nature of new innovations, and the limitations of the rural environment are such that fixed adoption costs do exist, in which case higher risk aversion among smaller farmers is a factor which can explain, by itself, the differential, farm-size dependent pattern of technology adoption observed.

Feder and O'Mara believe that risk aversion hinders adoption and that smaller farmers are more risk averse. These beliefs help explain how farm size relates to adoption.

Although there have not been many studies exploring the link between risk aversion and adoption, there is no consensus on the role risk aversion plays in adoption decisions.

Firm / Industry Characteristics

Turning from decision-makers to the firms themselves, it is important to look at characteristics of firms that lead some to adopt faster than others. It should be noted, however, that the distinction between decision-makers and firms is not always clear cut. When a firm has a single owner, socioeconomic characteristics of the firm blend with

those of the decision-maker. This is especially true in agriculture, where farms are often headed by one or very few individuals.

Size. In the economics literature, perhaps the most consistent factor associated with early adoption is firm size. In Roger and Stanfield's list of generalizations, firm size may relate to income and level of living. It has been suggested that larger firms can take advantage of returns to scale (Rahm and Huffman) or larger gross earnings (Karshenas and Stoneman). Larger firms are also less likely to face credit constraints because they have more collateral (Feder). Fixed costs in the form of information acquisition, loan fees, time to obtain materials, etc. together with lower levels of risk aversion in larger firms are also thought to lead these agents to adopt first (Feder and O'Mara). Differing perceptions and practices can also lead to differing adoption rates. Kivlin and Fliegel (p. 82) mention "...market opportunities, quality of farmland, and alternatives in farming decisions, which mostly favor large-scale operators." Romeo notes that large firms tend to have more equipment than small firms and will, therefore, have more equipment requiring replacement at any given time.

Empirically, firm size has been a factor associated with early adoption in many studies looking at different industries in various countries. Khanna finds farm size to positively relate to site-specific technologies in four Midwestern states. Kivlin and Fliegel find that larger-scale dairy farmers in Pennsylvania tend to adopt technologies faster than smaller-scale farmers. Lin finds farm size positively related to the speed at which Chinese farmers adopt hybrid rice. Negatu and Parikh find farm size is an important component in determining adoption rates in Ethiopia. The adoption of

improved cassava in Nigeria (Polson and Spencer) and the adoption of reduced tillage in Iowa (Rahm and Huffman) are found to be positively related to farm size. Further, the adoption of numerically controlled machines positively relates to firm size in ten different industries (Romeo). Some studies, however, find size not to be significant (Adesina and Baidu-Forson; Harper et al.), while others find it to be negatively related (Levin, Levin, and Meisel; Bisanda et al.; Gafsi and Roe).

Research and development expenditures. Firms that invest in research and development (R&D) are searching for improvements; therefore they may be more likely to adopt new technologies. Karshenas and Stoneman (p. 512) call R&D expenditures "... an indicator of a firm's ability to process information about the latest technologies arriving in the market." They find R&D expenditures to be positively related to the adoption of computer numerically controlled machine tools in Britain's engineering industry. Romeo finds that increased R&D investment speeds the adoption of numerically controlled machine tools in his study of ten industries. Rose and Joskow find R&D activity to speed technology adoption in the electric utility industry, as do Gibbs and Edwards in their study of British industry. On the other hand, Baptista does not find R&D expenditures to be positively related to adoption of microprocessors or computer numerically controlled machine tools. Studies examining R&D expenditures tend to look at industry rather than agriculture. Perhaps this is because most farmers do not conduct formal R&D, while most industries engage in some level of R&D. At the farm level, access to research by universities or others is perhaps important in the same way R&D is important at the industry level.

Land tenure or ownership structure. Several studies examine the role of land tenure among farmers and ownership structure of firms and how they relate to adoption. In their review, Feder and Umali cite several studies that conclude renters are less likely to adopt conservation practices than are landowners. Polson and Spencer find, however, that migrant farmers are more likely to adopt improved cassava in Nigeria than are landowners. They explain (p. 76), “Migrant farmers, because of their non-privileged position in the farming community in terms of access to land and other farm resources are more aggressive in their adoption of improved varieties.” Lee and Stewart find landowners to be less likely to adopt minimum tillage practices on cultivated cropland than other groups. They also find that non-family corporate structure does not significantly influence adoption decisions. In the same vein, Harper et al. do not find a significant relationship between Texas rice farmers’ adoption of integrated pest management techniques and whether the farm business is a partnership or a corporation. Caffey and Kazmierczak, on the other hand, find the adoption of new technology used in soft-shelled crab operations to be significantly related to a producer’s involvement in a full-time operation relying solely on family labor.

There is some controversy about the role of land tenure in semi-feudal situations. On one hand, landowners are also creditors and, therefore, have an incentive to prevent the adoption of technologies that would increase yields and reduce the indebtedness of the tenants. On the other hand, under feudalism, these landlords are powerful enough they could extract the rents from adoption. For example, they could evict their tenants and use hired labor to cultivate using the new technology. Sharecropping can hinder

adoption because of the moral hazard problem (Newberry). There is inherent uncertainty in the adoption of new technology. Landowners cannot observe sharecroppers' behavior; thus they do not want to risk losing the benefits. For a detailed description of the debate, see Feder, Just, and Zilberman (1985).

Other studies have looked at ownership structure and adoption of technology in industry. Rose and Joskow find, for example, that in the electric utility industry, investor-owned firms tend to adopt new technologies earlier than publicly-owned firms. Gibbs and Edwards find corporate status to positively relate to adoption decisions, with single plant enterprises adopting later. This finding may be related to size. Baptista does not find ownership structure to relate to microprocessor or computer numerically controlled machine tool adoption. There does not seem to be a consensus on the relationship between ownership and the adoption of technology.

Industry concentration. Several studies examine the relationship between industry concentration and the adoption of technology. While many of the other factors are applicable in industry and agriculture, there is more focus here on industry. Levin, Levin, and Meisel find higher seller concentration in the grocery industry retards the adoption of optical scanners. Romeo, in his study of ten industries, also finds innovation to spread less rapidly in more concentrated industries. Though Romeo claims he expected this result, he does not explain why.

Gort and Klepper find that technological change and the flow of information can impact market structure. Hannan and McDowell find that when larger firms adopt first, there is increased concentration, and when smaller firms adopt first, there is decreased

concentration. There is, therefore, disagreement on whether concentration or technological change comes first, but it appears that industry concentration is related to adoption, either as a cause or an effect. The relationship between industry concentration and technology adoption needs to be further studied.

Location. Location has been said to be important because of information spillovers. Baptista (p. 516) says, “Geographical proximity stimulates networking between firms, thereby facilitating imitation and improvement.” In a study of the adoption of computer numerically controlled machine tools and microprocessors, Baptista finds that regional learning effects are highly significant, and seem to be most important in the early stages of the diffusion process. There are two additional reasons for location to be important. First, firms need to have access to the supplies or services they need to adopt the technology. Khanna, for example, finds that farm location is important in the adoption of soil tests in the Midwest. Farms closer to locations providing the service are more likely to adopt. Second, agro-climatic conditions vary, and technologies developed in one location may not be as appropriate in another location. For example, Jansen, Walker, and Barker find that the adoption ceiling can be raised in India for modern coarse cereal cultivars only if regional conditions are taken into account. The places where the new cultivars are most beneficial have adopted them. Jansen, Walker, and Barker (p. 662) suggest, “The public sector could reallocate its resources to more location specific and difficult problems of the lagging adoption regions.”

Constraints. Agents wanting to adopt a new technology may face many legal, political, and social constraints. These constraints tend to be most prevalent in developing countries, though developed countries are not immune. Two constraints, labor and credit, have received the most attention in the literature.

Some new technologies reduce the need for labor, whereas others increase it. When facing labor shortages, farms or industries may be less likely to adopt labor increasing technologies and more likely to adopt labor saving technologies (Feder, Just, and Zilberman). Batz, Peters, and Janssen find that Kenyan dairy farmers, who face labor shortages, are unlikely to adopt technologies that require more labor. Labor shortages are also an issue in developed countries. Dorfman finds that off-farm labor supply is the most important factor relating to U.S. apple growers' decisions to adopt new technologies. The more time farmers spend working off their farms, the less likely they are to adopt new technologies. Caffey and Kazmierczak find similar results. Louisiana soft-shelled crab producers are more likely to adopt new technology if they work full-time on the farm. This is probably because their income solely depends on farming activities, giving them more incentive to try to increase net returns with improved technology.

Similarly, credit constraints can be a problem for small firms and those in developing countries. Feder, Just, and Zilberman find mixed results when examining how credit constraints actually impede adoption.

Characteristics of the Technology

Some studies focus exclusively on characteristics of the decision-maker or firm, other studies focus exclusively on the characteristics of the technology in question, and others look at both. Following is a summary of characteristics the literature has associated with technologies that are adopted quickly.

Profitability. Profitability is discussed in much of the early literature and assumed in most of the later literature. Economists generally assume that firms maximize profit. (Many of the studies deal with agriculture and, therefore, farmers. In many cases, expected utility maximization is the underlying assumption as opposed to profit maximization. Even so, there is no reason to assume adoption if there is no expected payoff.) Varying degrees of expected profit will lead to varied adoption dates. The first adopters assume the most risk because of imperfect information, but as more becomes known about the technology, the risk decreases. Also, the cost of new technologies often decreases as more firms adopt. Therefore, those with the most to gain will be willing to pay the higher price of early adoption. In his article on hybrid corn, Griliches (p. 516) states

Differences in the rate of acceptance of hybrid corn...are due at least in part to differences in the profitability of the changeover from open pollinated to hybrid seed. This hypothesis is based on the general idea that the larger the stimulus the faster is the rate of adjustment to it.

Related to the idea that adoption date is a function of profitability is Griliches's idea that firms supplying new technologies will supply them first in areas they expect to be most profitable. Even the availability of new technology may be a function of its profitability.

Caswell and Zilberman find that cost savings lead to the adoption of irrigation technologies in California. Mansfield (1973) finds profitability to relate to adoption in industry. In a study of farmers' decisions to adopt technology in the Altiplano region of Mexico, Byerlee and Hesse de Polanco point out that new technologies are often presented as a package. The package is pushed because there are positive interactions between the components. Capital constraints, however, prevent Mexican farmers from adopting the package all at once, so they adopt in a stepwise manner, beginning with the most profitable.

Essentially, empirical studies tend to 1) include profitability and find increased profitability positively related to the rate of adoption or 2) assume the technology is profitable and leave profitability out of the model. In no case, has anybody argued that adoption decisions are totally unrelated to perceived profitability.

Risk / uncertainty. Related to profitability are risk and uncertainty. Byerlee and Hesse de Polanco find Mexican farmers adopt technologies in order of profitability and risk. In the game theoretical literature, Hoppe finds there may be second-mover advantages because of the uncertain profitability in the adoption of a new technology. Jensen finds that uncertainty can lead both firms in a duopoly to choose not to adopt even when one firm's adoption would be socially optimal.

There are two issues in looking at the risk associated with new technologies. The technology may actually be risky or it may be perceived as risky. Whether decisions are based on perceptions or reality, the results are the same, and often studies focus on risk perceptions. Negatu and Parikh find perceptions about grain yield and marketability to

be very important in whether Ethiopian farmers adopt new technologies. Adesina and Baidu-Forson also find perceptions to be very important in the adoption of improved rice varieties in Burkina Faso and Guinea. Batz, Peters, and Janssen find Kenyan dairy farmers to be more likely to adopt technologies that promise a reduction in risk relative to traditional technologies. For farmers to adopt a new technology, these studies suggest the risk of failure must be lower than under the current technology. Kivlin and Fliegel find risk perceptions to relate to adoption decisions by dairy farmers in Pennsylvania. Technologies perceived to be riskier are adopted later.

Packaged technology / partial adoption. Many times technologies are divisible. Pieces can be adopted or the whole can be adopted on a small scale. Partial adoption is a way to minimize risk and learn by doing. More pieces of the technology may be adopted or the technology may be adopted more intensely as knowledge takes the place of uncertainty. Partial adoption is also a way for adopters to circumvent credit constraint problems and initial costs. Adopting part of a technology package will often have lower up-front costs than adopting everything at once. As discussed earlier, Byerlee and Hesse de Polanco find that Mexican farmers adopt technology packages in a step-wise fashion despite the fact that there are efficiency gains when the package is adopted as a whole. They adopt the most profitable and least risky parts first and then increase adoption as they can. Dorfman finds that U.S. apple-growers do not necessarily adopt all available technologies in a bundle, sometimes adopting only one. Khanna looks at the sequential adoption of soil testing and variable rate technology, which together increase productivity. She finds that some midwestern farmers adopt soil testing but not variable

rate technology. Farmers who adopt both do so because they gain the most from variable rate technology, but farmers who adopt only soil testing do so because they obtain relatively larger gains from soil testing.

The adoption of one technology can also impact the diffusion path of other technologies. Stoneman and Kwon find that when there are complementarities between new technologies, the adoption of one is affected by the price and number of users of the other. It appears that when technologies are packaged together, complements or divisible, they may be adopted in parts to reduce risk or to maximize expected utility. Technologies are interrelated, and so are their diffusion paths.

Adoption of Climate Forecast Information

While Chapter III examines technology adoption in general, Chapter IV is a case study of a specific, emerging technology, climate forecasts. This section provides the background for Chapter IV. The technology examined in Chapter IV is not a piece of equipment, but a piece of information. Just as an agricultural producer can decide to use a new piece of equipment, a producer can decide to use a new piece of information. The costs of equipment may be different from the costs of information, though both require learning. The uncertainty involved in adopting equipment may also be different than the uncertainty involved in adopting information. Uncertainty related to equipment may lessen over time, while the uncertainty related to information may not. Agrawala and Broad point out, for example, that each climate forecast is unique. The product changes. In addition, the performance of forecasts is uncertain. Agrawala and Broad (p. 7) conclude, “It is much harder to establish trust in seasonal forecasts despite repeated use

than it is in the case of other technologies.” Despite the differences in physical technology and information technology, both can be adopted or not adopted, and the adoption decision has profit ramifications.

The focus of the literature on climate forecast use differs somewhat from the rest of the adoption literature. One reason is that improved climate forecasts are relatively new. Only the earliest adopters are using the information. There has not been sufficient diffusion to estimate s-shaped curves. The literature has, therefore, focused on whether climate forecasts have economic value and on impediments to their use.

Use of Forecast Information

Though few studies look at the characteristics of those using climate information, several studies examine factors that may keep decision makers from using climate information (Glantz; Changnon, Sonka and Hofing; Washington and Downing; Callahan, Miles, and Fluharty; Klopper; Pulwarty and Redmond; Goddard et al.; Nicholls 1999). In some cases, information is lacking. Sometimes decision makers do not know the information is available (Changnon, Sonka, and Hofing), sometimes the information they receive is not useful (Goddard et al.; Callahan, Miles, and Fluharty), and other times (especially in developing countries) the information comes too late (Washington and Downing). One problem is that linkages between forecasters and potential users are not well developed (Pulwarty and Redmond; Goddard et al.; Klopper). Forecasters do not always collect or forecast the data most needed by economic agents or they do not present the information in a usable form.

In other cases, the problem is not a lack of information but an inability to interpret the information. Often decision-makers do not have training in atmospheric sciences and have a difficult time interpreting climate information (Chagnon, Chagnon, and Chagnon; Nicholls 1999; Pulwarty and Redmond). Even if the information is understood, it is often difficult to integrate climate forecasts into production decisions (Changnon, Sonka, and Hofing; Goddard et al.). Furthermore, the corporate structure or management environment is often sufficiently complex as to prevent the adoption of potentially useful climate information (Changnon, Sonka, and Hofing; Pulwarty and Redmond; Changnon, Changnon, and Changnon).

Related to the lack of training of decision-makers, is a general distrust or misunderstanding of climate forecasts and their potential value (Nicholls 1999; Changnon, Sonka, and Hofing). Decision makers' prior beliefs can also affect their willingness to use climate information (Letson et al.; Nicholls 1999). Nicholls (1999) states that people often use a rule of thumb when making decisions. They tend to regard evidence supporting prior beliefs as valid while disregarding evidence that goes against those beliefs. The sequence, framing, and quantity of information can affect a person's perceptions. Nicholls (1999) says "group-think" can play a role in decision making, as can primacy and inertia. Therefore, decision-makers do not always make decisions based on true probabilities but rather based on their intuition, which is often misleading (Mazzocco et al.).

Agrawala and Broad found similar impediments to adoption. In case studies of Peruvian fisheries during the 1997-1998 El Niño event and the 2000 Ethiopian Famine,

they found local beliefs to impact the use of climate forecasts. If forecasts went against local knowledge, they were not likely to be believed. Resource constraints also prevented the use of climate forecasts. Knowing there will be more fish does not help a fisherman who cannot afford new nets, has nowhere to store extra fish, or lacks markets in which to sell them. In addition, access to information is not uniform. Much climate information can be obtained on the Internet, but access is often unavailable in poor areas. Furthermore, climate forecasts have specificity effects. Regional forecasts may not be accurate on a farmer's land. These impediments are especially problematic in developing countries.

Easterling authored what may be the only study that statistically examines characteristics of climate forecast users. He finds that larger firms are more likely to use climate forecasts, as are decision-makers familiar with atmospheric science. This is in line with the adoption literature. On the technology side, Easterling finds forecast accurateness, lead-time, and skill in predicting extreme weather events positively related to climate information use.

For a more comprehensive study of the value and use of climate forecasts, interested readers are referred to the growing number of literature surveys (Goddard et al.; Wilks 1991; Global Climate Observation System; Nicholls 1996; Mjelde, Hill and Griffiths; Hill and Mjelde; Mjelde, Sonka, and Peel). These studies indicate that despite the fact that scientific and economic aspects of climate forecasting are still emerging, there is substantial evidence that use of climate forecasts in agricultural production decisions can have significant global welfare effects.

Conclusions

The sigmoid shape of the diffusion path has essentially become a stylized fact, though there is some debate about the most appropriate functional form or the reasons behind the shape. Most researchers agree that early adopters tend to have certain characteristics, but they disagree about what these characteristics are. While most studies show that education speeds adoption, there is less consensus on the roles of experience, age, outside links, and risk aversion. As far as firm or industry characteristics, size and in-house R&D tend to speed adoption while labor or credit constraints can hinder it. There are mixed results on the importance of land tenure and industry concentration. As far as technology is concerned, profitability positively relates to adoption, and risk / uncertainty initially lead to partial or low intensity adoption. In addition, when technologies are related, the diffusion path of one can affect the diffusion path of others. These are general results. All of them have been disputed in at least one study.

CHAPTER III

UNIVERSALITY OF FACTORS AFFECTING TECHNOLOGY ADOPTION: A META-ANALYTIC APPROACH

Many disciplines have contributed to the enormous body of literature on technology adoption. Rogers and Stanfield, for example, found 708 empirical studies published before 1970. Three decades later, this number can only be higher. The vast majority of these publications, however, examine the adoption of an individual technology in a specific geographical area, making it difficult to draw general conclusions. In addition to varied technologies and locations, studies vary in their methods, data, and explanatory variables. It is hardly surprising that results also vary widely. Even for the same type of technology, results are often conflicting. In the case of soil conservation technologies, for example, some studies find education to be positively related to adoption (D'Souza, Cypers, and Phipps; Lapar and Pandey; Warriner and Moul), some studies find education to be unrelated to adoption (Adesina and Baidu-Forson; Comer et al.; Shiferaw and Holden), and others find education to be negatively related to the adoption of soil conservation technologies (Gould, Saupe, and Klemme; Norris and Batie). Outreach effort, farm size, and age are other examples of variables whose affect on technology adoption have produced conflicting results in the published literature.

Reading this literature, one is left wondering if any general conclusions can be drawn (see Feder, Just, and Zilberman; Marra, Pannell, and Ghadim for reviews of the technology adoption literature). Is the variation caused by socio-economic, cultural, or historical differences or is the variation due to methodological differences? In other

words, is there information researchers can provide technology-promoters to help them identify potential adopters? Technology plays a central role in economic theory, especially in the areas of growth, development, and natural resources. If improved technology leads to economic growth and development, as well as a healthier planet, technology adoption should be encouraged. *A priori* knowledge of who is likely to adopt technology would allow technology-promoters to target particular economic agents. As the availability of funds earmarked for development or the environment continues to decrease, such targeting becomes increasingly important.

The objective of this chapter is to understand who is likely to adopt new agricultural production technologies to help technology-promoters target producers most likely to adopt technologies. To meet this objective, the concept of universality is defined. Then a statistical test for universality is introduced. Meta-regression-analysis (MRA) is used to test four factors identified in the literature as affecting technology adoption. Two factors (age and education) are specific to the producer, while one (farm size) is related to the firm. The last factor (outreach) is related to the external context in which the firm operates.

Factors Examined

Age, education, outreach, and farm size are the four most common factors included in adoption models of agricultural technology, but there is disagreement about how they relate to the adoption of technology. Each factor has been shown to have a positive significant, negative significant, and insignificant relationship with technology adoption. Most researchers believe *a priori* that education positively relates to technology

adoption. Nelson and Phelps (p. 70) sum up the sentiment saying, “Educated people make good innovators, so that education speeds the process of technological diffusion.” Farm size is also believed *a priori* to promote technology adoption. Farm size is often used as a proxy for income. Larger farms may indicate higher incomes or economies of scale. Higher incomes may make adoption more feasible, while economies of scale may make adoption more profitable. Education and farm size tend to be positive and significant in most studies, but not all. Conclusions on age and outreach vary more. Older people may be less willing to try new things than their younger counterparts. On the other hand, older people may be more experienced or wealthier, which may make them more willing to try new technologies. The expectation is that outreach leads to adoption through the dissemination of information concerning new technologies.

Methodology – Meta-Analysis

Meta-analysis is used to draw general conclusions from previous studies (Stanley 2001). Results from previous studies are analyzed statistically to help explain variation across studies and to test for generalizations. Here, a meta-regression analysis (MRA), simply a meta-analysis using regression analysis, is performed on studies examining the adoption of agricultural production technologies to see whether any of the four factors are systematically related to technology adoption across geographic location and type of technology. Such factors are called universal. The definition and test for universality is discussed later.

Procedures

Stanley (2001) suggests the following steps for conducting an MRA. First, all relevant studies need to be identified and included in the analysis to reduce potential bias caused by a non-random selection of studies. If an author includes only his favorite studies or studies with results that conform to his preconceived hypotheses, the results of the meta-analysis are biased. Second, a summary statistic must be chosen that converts the evidence into a common metric. Stanley (2001) suggests using the standard normal test statistic because most statistics can be easily converted to this unitless metric. This summary statistic is the dependent variable used in the MRA. Third, independent variables are selected, which include study characteristics as well as variables included in the studies. Finally, one conducts the regression analysis and draws inferences. These four general steps are followed in the analysis described in this paper.

The first step is to identify the relevant literature, which, in this case, is defined as empirical studies using regression analysis to examine the adoption of agricultural production technologies. While hundreds of studies have examined technology adoption, some are not empirical in nature (Abara and Singh; Culver and Seecharan), and others, though empirical, provide insufficient information on variable measurement or use methods that cannot be converted to a summary statistic (Moser and Barrett; Sturm and Smith). In addition, many studies deal with consumer goods or non-agricultural production goods (Baptista; Lal; Levin, Levin, and Meisel). While there is nothing wrong with studying non-agricultural technologies, the objective of this study revolves around agriculture. Furthermore, some empirical studies of agricultural

technologies do not include any of the four factors as independent variables in their models (Garst; Lynne, Shonkwiler, and Rola). While these studies qualify as part of the relevant literature, they do not produce any observations for the MRA's. For these reasons, many studies on technology adoption are excluded from the sample.

While some studies only report results from their final model, other studies report many sets of results. Using all reported results in the MRA puts additional weight on studies reporting multiple results. For this reason, Stanley (2001) suggests using only one set of results per study. A number of studies, however, examine several types of technologies or examine technology adoption in more than one location. For studies examining multiple technologies or locations, using one set of results would be throwing out information. The decision was made to use one set of results for each study unless results are reported for multiple technologies or locations, in which case, one set of results for each technology and / or location is used. When multiple sets of results are reported for a given technology or location, the results associated with the model containing the largest number of independent variables are used. The 107 studies that met the requirements to be included in the MRA contained 170 relevant regression analyses. From this point forward, "study" refers to the previous papers used in the MRA (of which there are 107), while "analysis" refers to a particular set of results from a study (of which there are 170). "Model" refers to the MRA model.

Identification of a common metric to be used as the dependent variable constitutes the second step of MRA. To better understand how age, education, outreach, and farm size relate to technology adoption, standard normal statistics (z-scores) are

obtained from previous analyses' reported results on the four factors. The z-scores are then used as the dependent variables in the MRA analyses. In each analysis, the dependent variable is some measure of technology adoption, while the independent variables are producer and technology characteristics. The reported results for each factor in each analysis are converted to a z-score. As expected, studies are not consistent in the statistical results they report. Studies report individual f -statistics, chi-squared (χ^2), t -statistics, or the estimated coefficients and their standard errors or p -values. These different statistical measures are converted to z-scores as follows. When the study reports an individual f -statistic, distributed $F(\nu_1, \nu_2)$, the f -statistic is converted directly to a z-score using equation (3.1). If a t -statistic is given, the t -statistic is squared, resulting in an f -statistic, where $\nu_1 = 1$. The z-score is then obtained using equation (3.1). When a study reports an estimated coefficient and its standard error or p -value, these are used to obtain a t -statistic, which is converted to a z-score as described above. If a study reports a χ^2 -statistic with ν degrees of freedom, the z-score is obtained using equation (3.2). These equations are from Stanley 1998

$$(3.1) \quad z_{i,j} = \frac{f^{1/3} (1 - 2/(9\nu_2)) - (1 - 2/(9\nu_1))}{(2/(9\nu_1) + f^{2/3} 2/(9\nu_2))^{1/2}}$$

$$(3.2) \quad z_{i,j} = \frac{(\chi^2 / \nu)^{1/3} - (1 - 2/(9\nu))}{(2/(9\nu))^{1/2}},$$

where $z_{i,j}$ is the z-score for the j th factor in the i th analysis. Intuitively, the z-score is an indication of whether there is a relationship between the factor (age, education, outreach,

or farm size) and technology adoption. Higher z-scores indicate a stronger relationship, while low or negative z-scores indicate a weaker relationship.

The third step in performing a meta-analysis is to determine the independent variables to be included in the MRA models. There are two types of independent variables: 1) characteristics, which have to do with aspects of the analysis such as location and sample size and 2) included variables, which indicate which variables were included in the regression analysis. Characteristics included in the MRA model are: methodology, location, type of technology, year of data collection, and sample size. The first three are 0 / 1 qualitative variables, while the last two are count variables. Including methodology variables allows examination of whether the modeling approach used in previous studies has systematically affected the statistical significance of the four factors. Location variables are used to indicate whether factors affecting adoption in one area also affect adoption in other areas. In a similar way, including technology type allows examination of whether technologies are adopted differently. The year of data collection is used to determine whether the importance of the factors has changed over time. Sample size variables are included to test for universality, as discussed below.

MRA can also determine whether the inclusion of certain variables in previous analyses systematically affected the predicted relationship between age, education, outreach, or farm-size and technology adoption. Zero / one qualitative variables are used to indicate whether the following variables were included in the analysis: income, age, education experience, outreach, labor constraint, land quality, land tenure, other social

variable, and other resource constraints. *Other social* and *other resource* include any variable not accounted for in the other eight categories.

The four, individually estimated MRA models are of the form:

$$(3.3) \quad z_{i,j} = f(c_{i,j}^+, c_{i,j}^-, X_j, Q_j, G_j) + e_{i,j} \quad \text{for } j = 1, 2, 3, 4$$

where

$z_{i,j}$ is the z-score obtained from the i th analysis for the j th factor,

$c_{i,j}^+$ is the sample size if the i th analysis found a positive relationship between the j th factor and technology adoption and zero otherwise (discussed later),

$c_{i,j}^-$ is the sample size if the i th analysis found a negative relationship between the j th factor and technology adoption and zero otherwise (discussed later),

X_j is a matrix of k characteristics used to test for universality (discussed later),

Q_j is a matrix containing the remaining r characteristics,

G_j is a matrix of included variables indicating whether the l th variable was included in the i th analysis, and

$e_{i,j}$ is the random error.

Estimation

Ordinary Least Squares (OLS) and minimum absolute deviation (MAD) are used to estimate the models. MRA often suffers from heteroskedasticity, which can lead to biased inference (Smith and Huang). White's test for heteroskedasticity indicated a potential problem in all four MRA models, so White's robust estimator is used when estimating with OLS. The estimated coefficients are the same as OLS, but the robust

estimator results in a heteroskedasticity consistent estimate of the asymptotic covariance matrix. This estimator is important because, as Greene (p. 505) explains, “It implies that without actually specifying the type of heteroskedasticity, we can still make appropriate inferences based on the results of least squares.”

Because OLS estimation squares the error terms, outliers are weighted heavily. Examination of the data indicated a number of observations that were causing the distribution of the error terms to have fat tails. Kennedy (p. 299) explains, “If the distribution of the errors is ‘fat-tailed’ . . . , although the OLS estimator is BLUE, it is markedly inferior to some nonlinear unbiased estimators.” Kennedy suggests using a “robust” estimator, of which MAD is one. Greene (p. 308) says, “The least squares estimator can be seriously distorted by outlying observations in a relatively small sample, while the minimum absolute deviations (MAD) estimator will be considerably less so.” Koenker and Bassett agree MAD is preferred to OLS when outlying observations cause the errors to have fat tails. The difficulty with the MAD estimator, however, is that there is no simple way to correct for heteroskedasticity. A trade-off exists. The estimated variance may be biased due to outliers when using OLS estimators and biased due to heteroskedasticity when using MAD estimators. In either case, inference involving the estimated variance may be problematic. Following Smith and Huang, both sets of results are presented.

Universality: Definition and Test

In addition to explaining variation in results from previous studies, MRA allows for general conclusions to be drawn, the primary concern of this study. Specifically, the

MRA tests whether age, education, outreach, and farm size are universal factors leading to the adoption of agricultural technology. A universal factor is defined as a factor that is systematically related to technology adoption across geographic locations and types of technologies. To enrich the concept of universality, strength and direction are added. A factor can be strongly positive universal, strongly negative universal, weakly positive universal, weakly negative universal, or not universal. A positive universal factor fosters technology adoption, while a negative universal factor hinders it. Strongly universal factors impact technology adoption in the same way regardless of geography and technology type. Weakly universal factors impact technology adoption, but the magnitude of the impact varies by geography and / or technology type. Factors are not universal if they have no systematic relationship to technology adoption.

The test for universality involves two steps. First, it must be determined if the factor is universal (positive or negative) or not universal. If a factor is universal, a second test determines the strength of universality (strong or weak). In the first step, the relationship between the sample sizes of the analyses and the z-scores is examined. A positive and significant relationship indicates that as the number of observations in the analyses increases, the z-scores tend to increase, or become more significant (Stanley 1998). Previous meta-analyses have stopped here. Previous meta-analyses have only been concerned with the inference on the sample size variable and not the direction. Because universality is directional, this study expands the test used in previous studies so direction can be examined.

The z-score is a function of the f -statistic or χ^2 -statistic, both of which are positive, regardless of the sign associated with the estimated coefficient. The z-score, therefore, indicates the strength of the relationship between the factor and technology adoption but not the direction. To understand the direction, two sample size variables are used in the MRA. *Positive sample* refers to the sample size of the analysis if a positive relationship between the factor and technology adoption was found. *Negative sample* refers to the sample size of the analysis if a negative relationship was found. A positive and statistically significant coefficient on exactly one sample size variable is a necessary condition for strong universality and a sufficient condition for weak universality. The direction of the universality relationship depends on the inference on both sample size variables (table 3.1). An insignificant coefficient indicates there is no relationship between the sample size and the z-score, while a negative coefficient indicates that as the sample size increases, the z-score becomes less significant. Insignificant and / or negative coefficients indicate that a factor is not universal. If the two estimated sample size coefficients are negative, insignificant, or any combination of negative and insignificant, the factor is not universal. If both estimated coefficients are positive and statistically significant, the direction of universality is indeterminate. As the sample size increases, the relationship between the factor and technology adoption becomes more positively and negatively significant. It is, therefore, impossible to draw a general conclusion. Universality occurs when one coefficient is positive and significant, while the other coefficient is either insignificant or negative. The factor is universal in the direction of the significant coefficient (table 3.1).

Table 3.1. Universality Test Given Inference on the Coefficients Associated With the Positive and Negative Sample Size

		Positive Sample Size Coefficient			
		Significant Positive	Insignificant Positive	Insignificant Negative	Significant Negative
Negative Sample Size Coefficient	Significant Positive	?	U ⁻	U ⁻	U ⁻
	Insignificant Positive	U ⁺	NU	NU	NU
	Insignificant Negative	U ⁺	NU	NU	NU
	Significant Negative	U ⁺	NU	NU	NU

Positive sample size coefficient refers to the group of analyses in which the coefficient on the factor is positive, and negative sample size coefficient refers to the group of analyses where the coefficient on the factor is negative. A ? indicates that the direction of universality cannot be determined, U⁻ is negative universal, U⁺ is positive universal, NU is not universal.

If a factor is universal, the strength is determined by the second step. The null hypothesis is that the coefficients on the geography and technology variables are jointly zero. If the coefficients are jointly zero, the factor impacts technology in the same way in all locations and for all types of technologies. Not rejecting the null hypothesis indicates strong universality, while rejecting the null indicates weak universality. A Wald (χ^2) test is used to test whether the coefficients on Latin America, Asia, Africa, land technologies, and information technologies are jointly equal to zero. (Developed country and input technology categories were dropped to avoid perfect collinearity. See the next section for clarification.) An insignificant χ^2 -statistic indicates a factor is strongly universal, while a significant χ^2 -statistic indicates weak universality. For factors that are weakly universal, t -statistics are used to determine which locations and / or which types of technologies tend to have different z-scores.

Table 3.2. Number of Analyses Conducted in Each Country

Developed Countries	Number	Africa	Number	Asia	Number	Latin America	Number
Australia	1	Burkina Faso	4	Bangladesh	3	Brazil	20
Canada	5	Cameroon	2	China	1	Guatemala	1
Greece	1	Ethiopia	10	Fiji	1	Honduras	1
Israel	1	Ghana	3	India	12	Mexico	2
U.S.	62	Ivory Coast	1	Indonesia	1	Panama	2
		Guinea	1	Nepal	1	Peru	2
		Malawi	1	Pakistan	3		
		Niger	1	Philippines	7		
		Nigeria	5				
		Sierra Leone	1				
		Swaziland	2				
		Tanzania	10				
		Tunisia	2				
Total	70		43		29		28

Data

Results from 170 analyses conducted in 32 countries are used in the MRA (table 3.2).

Technologies analyzed in the studies are divided into three types: inputs, land, and information (table 3.3). The largest number (100) deals with input technologies. Most, like hybrid seeds, fertilizers, and pesticides, are variable inputs used in crop production. Seven analyses, however, examine the adoption of fixed inputs (equipment), while four in developing countries look at animal traction. One analysis focuses on manure testing,

which relates to fertilizer use and was thus put into the input category. (One could argue that manure testing is an information technology, but when this analysis was coded as an information technology, the inference did not change for any of the four MRA's.) Five analyses examine bST, an input used on dairy farms.

Table 3.3. Number of Analyses of Each Technology Type

Input	Number	Land	Number	Information	Number
Hybrid Seeds	39	Min/No Tillage	17	Computer	8
Fertilizers	25	Erosion Prevention	17	Financial Statements	4
IPM	13	Land Enhancing	7	Forward Pricing	1
Pesticides	6	Irrigation	4	Consulting Service	2
Equipment	7	Soil Testing	5		
Animal Traction	4	Pasture Rotation	1		
bST	5	Pasture Burning	2		
Manure Testing	1	Laser-leveling	1		
		Direct Seeding	1		
Total	100		55		15

Land technology, the second largest group (55), is defined as any technology directly involving the land that does not fall into the input category. The majority have to do with soil conservation, though irrigation, soil testing, laser-leveling, and direct seeding are also represented. Soil testing is placed into the land category because of its obvious involvement with the land. (One could also argue it belongs in the information

category. When the five analyses on soil testing were coded as information technologies, the inference changed very little. The one slight change is discussed in the results section. In the same way, one could argue that irrigation technologies belong in the input category. Classifying the irrigation analyses as inputs did not change the inference.) Direct seeding refers to "...wet seeding of pregerminated seed on puddle soils in banded paddy fields" (David and Otsuka p. 137) and is included in land technology because it has to do less with the seed itself than with the conditions under which it is put in the land. Also in the land category are three analyses concerned with pasture management; two look at burning and one looks at rotation. The smallest group of analyses (15) examines information technologies. Eight examine computer adoption, four look at the use of financial statements, one examines forward pricing usage, and two look at the use of consultants.

Summary statistics are presented in table 3.4. *Whole sample* refers to all 170 analyses included in at least one of the four MRAs. The four subsamples include only analyses used in the individual MRA. For example, only 78 analyses out of 170 included age, while 116 included education. Mean z-scores give an indication of whether there is a relationship between age, education, outreach, and farm size and technology adoption. The means, however, do not take the variation into account (Stanley 1998). The means and standard deviations of the sample may be high considering the standard normal distribution has a mean of zero and a variance of one.

Table 3.4. Summary Statistics of Data Used in Meta-Regression Analyses

	Statistic	Whole Sample	Age	Education	Outreach	Farm Size
Number of Observations		170	78	116	76	118
z-score	mean	-----	1.78	1.11	1.90	1.63
	st. dev.	-----	(4.15)	(2.01)	(4.10)	(1.93)
<i>Sample Size Variables</i>						
Analyses with Positive Coefficients	analyses	-----	41	104	67	99
Sample Size (c ⁺)	mean	-----	292	349	262	429
	st. dev.	-----	(217.99)	(324.36)	(180.10)	(805.77)
Analyses with Negative Coefficients	analyses	-----	37	12	9	19
Sample Size (c ⁻)	mean	-----	287	193	264	152
	st. dev.	-----	(402.50)	(179.53)	(288.66)	(223.45)
<i>Characteristics</i>						
Year of Data Collection	mean	1989	1990	1989	1990	1988
	st. dev.	(7.87)	(6.00)	(7.23)	(6.02)	(8.49)
Linear Model	analyses	27	9	18	8	18
Dichotomous	analyses	122	57	87	56	88
Tobit	analyses	21	12	11	11	12
Developed	analyses	70	32	50	32	56
Latin America	analyses	28	17	22	17	18
Africa	analyses	43	19	26	19	28
Asia	analyses	29	12	20	10	18
Input Technology	analyses	100	44	70	42	73
Land Technology	analyses	55	25	35	25	32
Information Tech.	analyses	15	9	11	3	13
<i>Included Variables</i>						
Income	analyses	142	69	97	60	118
Age	analyses	72	78	55	43	62
Education	analyses	103	56	116	59	84
Experience	analyses	55	17	46	25	40
Outreach	analyses	63	45	58	76	49
Labor Constraint	analyses	70	35	58	37	51
Land Quality	analyses	87	45	73	50	72
Land Tenure	analyses	41	22	29	14	34
Other Social	analyses	108	49	73	49	76
Other Resource	analyses	115	42	83	52	79

“Analyses” means the summary statistic is the number of analyses with the relevant characteristic.

Analyses with positive coefficients and analyses with negative coefficients

indicate the number of analyses reporting positive / negative coefficients for each factor.

Most analyses showed education, outreach, and farm size to be positively related to

technology adoption, while the results on age were somewhat mixed. *Sample size* varies substantially with the mean sample size for analyses with positive coefficients (c^+) ranging from 262 for outreach to 429 for farm size and the mean sample size for analyses with negative coefficients (c^-) ranging from 152 for farm size to 287 for age. All standard deviations are above 179. It is interesting to note that the analysis with the smallest sample has only 22 observations, while the largest has 7,649.

Under characteristics, the mean *year of data collection* is 1989 for the whole sample, and within one year of 1989 for each of the subsamples. Though two studies were performed in the 1940's, the majority were conducted in the 1980's and 90's (figure 3.1). Data for the most recent study were collected in 2002. The remaining variables are zero / one variables indicating features present or absent in each analysis.

The first set of variables deals with the methodology used in the study. *Linear model* indicates that the study uses a linear model. In some studies using linear models, the dependent variable is the percentage of hectares or acres on which the technology is adopted. Other studies use an index of technology adoption as the dependent variable. The index refers to how frequently the technology is used (Napier, Thraen, and Goe) or the number of technologies used (Voh). *Tobit* refers to studies where the dependent variable is the percentage of acres or hectares on which the technology is used, and the author uses Tobit analysis. This type of variable measures the extent of adoption as opposed to adoption versus nonadoption. If the coefficient associated with the Tobit variable is significant, there is an indication that the relationship between the factor and adoption intensity may differ from the relationship between the factor and initial

adoption. Finally, *dichotomous* indicates the study uses a zero / one dummy variable as the dependent variable. These studies use probit, logit, Heckman's (first stage), or Gompertz curve as the basis for their analysis. The *dichotomous* variable is dropped to avoid perfect collinearity. The coefficients on the other methodology variables are interpreted as the difference from dichotomous studies.

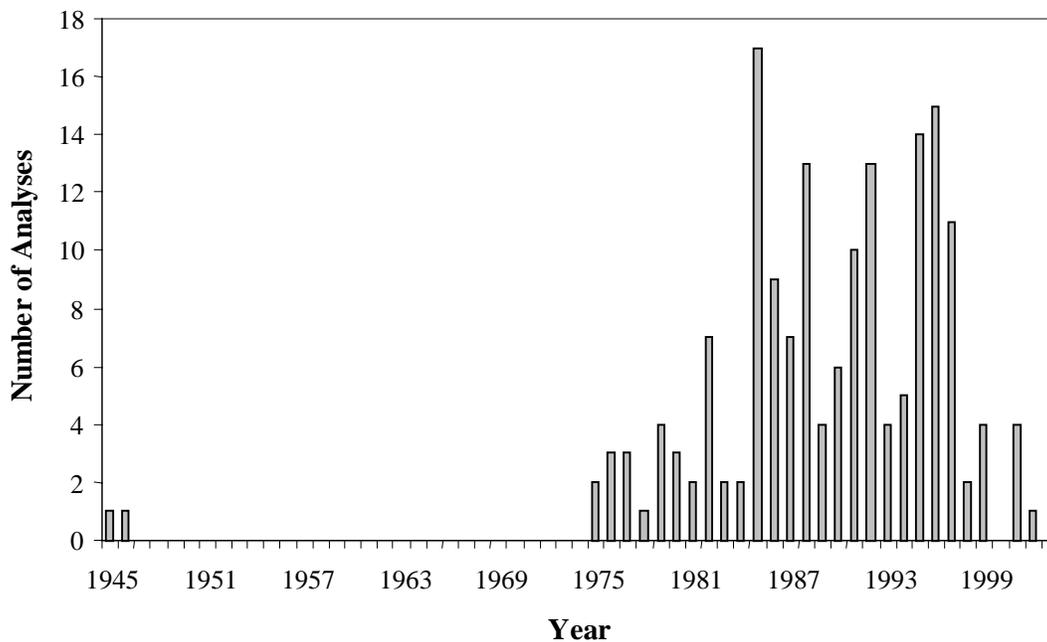


Figure 3.1. Number of analyses conducted in each year

The next set of variables relates to the location of the analysis: *developed* country, *Latin America*, *Africa*, or *Asia* (table 3.2). The *developed* variable is dropped in the estimation procedure. The third set of variables, *input*, *land*, and *information*,

indicates the type of technology, as defined in table 3.3. The *input* variable is dropped when estimating the MRA's.

The remaining variables indicate which explanatory variables are included in each analysis. Socio-economic variables are *income*, *age*, *education*, *experience*, and *land tenure*, while resource variables are *outreach*, *labor constraints*, and *land quality*. *Other social* and *other resource* indicate that some variable outside of the above categories was included. It should be noted that farm size is often used as a proxy for income, so the *income* variable includes analyses using farm size or monetary income. Appendix A contains a list of the studies used in the meta-analysis.

Results and Discussion

Age

Results for the age model are presented in table 3.5. Using OLS, the coefficients on both *sample size* variables are insignificant, indicating age is not universal. Age may not be related to technology adoption. Using MAD, both *sample size* coefficients become significant. *Positive sample size* is negatively significant, while *negative sample size* is positively significant. Using the universality test illustrated in table 3.1, age is negative universal. Older people are generally less likely to adopt technology than younger people. The *p*-value associated with the Wald test for strong universality in the MAD results is 0.11. If one chooses a significance level greater than 0.11, the MAD results indicate age is weakly negative universal. At lower significance levels, age is strongly negative universal. In addition, the *t*-statistics from the MAD model show analyses conducted in Latin America tend to have lower z-scores relative to analyses conducted in

developed countries. The MAD results also find that analyses on information technologies generally have lower z-scores than input technology analyses. Both OLS and MAD find that using a linear model tends to increase age's z-score, making age appear more significantly related to technology adoption. In addition, the inclusion of education increases age's z-score, while the inclusion of land tenure decreases age's z-score.

Table 3.5. Meta-Regression Analysis Results for Age

Independent Variables	OLS		MAD	
	Coefficient	<i>t</i> -statistic	Coefficient	<i>t</i> -statistic
Intercept	-5.14	-0.03	72.76	0.98
<i>Variables Used in Universality Test – First Step</i>				
Positive Sample Size	-0.38	-1.39	-0.22	-2.02*
Negative Sample Size	0.19	0.91	0.13	1.97**
<i>Variables Used in Strength Test</i>				
Latin America	-1.89	-1.25	-1.23	-1.66***
Africa	-0.23	-0.24	-.63	-0.99
Asia	0.45	0.36	.11	0.16
Land Technology	-0.67	-0.67	.03	0.06
Information Tech.	-0.49	-0.40	-1.35	-1.84**
<i>Wald test for Strength of Universality – Second Step</i>				
	χ^2 -statistic	<i>p</i> -value	χ^2 -statistic	<i>p</i> -value
	0.99	0.32	2.44***	0.11
<i>Other Variables</i>				
Independent Variables	Coefficient	<i>t</i> -statistic	Coefficient	<i>t</i> -statistic
Year of Data Collection	0.00	0.03	-.04	-0.97
Linear Model	8.07	2.26*	1.65	2.34*
Tobit	-0.93	-0.80	-.84	-1.38
Income	-0.39	-0.25	-.77	-1.18
Education	1.67	1.60***	1.05	2.13*
Experience	1.68	1.03	.25	0.35
Outreach	0.29	0.31	-.34	-0.71
Labor Constraint	1.08	1.14	.72	1.36
Land Quality	1.78	1.60	.60	1.33
Land Tenure	-2.75	-2.41*	-.82	-1.61***
Other Social	0.46	0.60	.39	0.87
Other Resource	-0.47	-0.47	-.26	-0.51
R^2	.44		.23	

Note: Sample size is in hundreds of observations, *** is significant at the 15% level, ** is significant at the 10% level, and * is significant at the 5% level.

Education

In both the OLS and MAD estimations, the coefficients on *positive sample size* are positively significant, while those on *negative sample size* are insignificant, indicating education is a positive universal factor in technology adoption (table 3.6). The Wald test indicates education is strongly universal using OLS but weakly universal using MAD.

Table 3.6. Meta-Regression Analysis Results for Education

Independent Variables	OLS		MAD	
	Coefficient	<i>t</i> -statistic	Coefficient	<i>t</i> -statistic
Intercept	-42.68	-0.88	-37.37	-1.05
<i>Variables Used in Universality Test – First Step</i>				
Positive Sample Size	0.16	2.68*	0.12	3.37*
Negative Sample Size	0.52	1.27	0.01	0.05
<i>Variables Used in Strength Test</i>				
Latin America	-1.05	-1.64***	-1.65	-4.05*
Africa	-0.41	-0.73	-0.32	-0.89
Asia	0.19	0.29	-0.96	-2.77*
Land Technology	-0.13	-0.27	-0.29	-1.11
Information Tech.	0.05	0.07	0.86	2.05*
<i>Wald test for Strength of Universality – Second Step</i>				
	χ^2 -statistic	<i>p</i> -value	χ^2 -statistic	<i>p</i> -value
	0.48	0.49	3.85*	0.05
<i>Other Variables</i>				
Independent Variables	Coefficient	<i>t</i> -statistic	Coefficient	<i>t</i> -statistic
Year of Data Collection	0.02	0.93	0.02	1.10
Linear Model	0.20	0.37	0.30	0.88
Tobit	0.62	0.79	0.42	1.11
Income	-0.92	-1.63***	-0.97	-3.16*
Age	-0.23	-0.62	0.36	1.55***
Experience	-0.47	-1.21	-0.62	-2.46*
Outreach	0.08	0.19	-0.10	-0.40
Labor Constraint	0.10	0.27	0.41	1.64***
Land Quality	-0.70	-1.56***	-0.42	-1.60***
Land Tenure	-0.81	-1.60***	-0.71	-2.59*
Other Social	-0.56	-1.47***	-0.09	-0.37
Other Resource	0.45	1.01	0.25	0.90
R^2	.35		.24	

Note: Sample size is in hundreds of observations, *** is significant at the 15% level, ** is significant at the 10% level, and * is significant at the 5% level.

The t -statistics from the OLS model show education to be somewhat less important in Latin America, with a p -value of 0.10. While the joint test indicates strong universality, individual tests indicate that education is on the border of weak universality. The MAD results show education to be less important in Latin America and Asia. The MAD model also shows education to be more important in the adoption of information technologies than input technologies. When analyses on soil testing are coded as information technologies, however, this result changes, and the coefficient associated with information technologies becomes insignificant. In other words, education may be more important for some types of information than others. Furthermore, the presence of *income*, *experience*, *land quality*, and *land tenure* variables in a regression analysis tend to negatively influence the predicted relationship between education and technology adoption, while the presence of *age* or a *labor constraint* variable tends to increase the predicted relationship.

Information technologies such as computers may require more education than input technologies. A minimum level of education may be needed to adopt even low levels of technology. Once that level is reached, low and medium levels of technology can be adopted. Only for high levels of technology is more education needed. Africa may not have the education necessary for adopting even the lowest levels of technology, while Latin America and Asia do. As higher-tech technologies are introduced in Latin America and Asia, the need for education may increase. Inclusion of socio-economic variables like *income*, *experience*, and *land tenure* may lessen the predicted relationship between education and technology adoption because they are related. More educated

people may have higher incomes, more experience, and own land. Leaving these socio-economic variables out of a regression analysis may add some of their effect to the estimated coefficient on education, making the impact of education appear larger. The inclusion of *age* may slightly increase the z-score on education, though the effect is only significant in the MAD model and has a *p*-value of 0.13.

Outreach

In table 3.7, neither *sample size* coefficient is significant using OLS or MAD. Outreach is not a universal factor. In general, outreach does not appear to be important in technology adoption decisions. Asia is significant in both models, indicating outreach may be more important in Asia than in developed countries. In addition, OLS results indicate that the importance of outreach may be increasing over time. Linear models increase the z-scores associated with outreach, as do the inclusion of *age* or *experience* variables. *Tobit* models may slightly decrease the z-scores, indicating that outreach may have more impact on the initial adoption decision than on the extent of adoption. These results indicate that outreach agents may want to alter their approach. Though the impact of outreach may be somewhat higher in Asia than other places, and the impact may be increasing over time, outreach agents do not seem to be a primary factor in the decision to adopt new technology.

Table 3.7. Meta-Regression Analysis Results for Outreach

Independent Variables	OLS		MAD	
	Coefficient	<i>t</i> -statistic	Coefficient	<i>t</i> -statistic
Intercept	-357.86	-2.07**	-15.73	-0.18
<i>Variables Used in Universality Test – First Step</i>				
Positive Sample Size	0.12	0.46	-0.02	-0.17
Negative Sample Size	-0.06	-0.24	-0.15	-0.92
<i>Variables Used in Strength Test</i>				
Latin America	0.88	0.55	-0.95	-1.15
Africa	-0.15	-0.12	0.61	0.84
Asia	2.12	1.66***	0.96	1.55***
Land Technology	-1.14	-1.18	0.08	0.17
Information Tech.	0.06	0.05	-1.11	-1.02
<i>Wald test for Strength of Universality – Second Step</i>				

Test not performed because outreach failed first step of test for universality

Independent Variables	<i>Other Variables</i>			
	Coefficient	<i>t</i> -statistic	Coefficient	<i>t</i> -statistic
Year of Data Collection	0.18	2.06*	0.00	0.20
Linear Model	7.76	2.22*	0.74	1.17
Tobit	-1.10	-1.11	-0.92	-1.58***
Income	0.48	0.61	0.24	0.47
Age	1.86	2.05*	0.51	1.28
Experience	2.31	2.06*	0.78	1.66***
Education	-0.65	-0.69	-0.49	-0.89
Labor Constraint	0.13	0.14	0.10	0.21
Land Quality	-0.07	-0.11	-0.49	-1.08
Land Tenure	-1.04	-0.71	-0.65	-1.05
Other Social	0.73	0.72	0.25	0.50
Other Resource	-0.28	-0.30	-0.03	-0.06
R^2	.43		.04	

Note: Sample size is in hundreds of observations, *** is significant at the 15% level, ** is significant at the 10% level, and * is significant at the 5% level.

Farm Size

Positive sample size is highly significant in both the OLS and MAD models, while *negative sample size* is not, making farm size a positive universal factor (table 3.8). The significance of *year of data collection* indicates the importance of farm size is increasing over time. The Wald test using OLS indicates strong universality. Using MAD, however, the Wald test indicates weak universality. The MAD model finds *Asia* and

Table 3.8. Meta-Regression Analysis Results for Farm Size

Independent Variables	OLS		MAD	
	Coefficient	<i>t</i> -statistic	Coefficient	<i>t</i> -statistic
Intercept	-94.48	-2.19*	-78.29	-2.27*
<i>Variables Used in Universality Test – First Step</i>				
Positive Sample Size	0.05	2.34*	0.04	2.61*
Negative Sample Size	-0.13	-.83	0.07	0.54
<i>Variables Used in Strength Test</i>				
Latin America	0.33	0.50	-0.16	-0.37
Africa	-0.21	-0.42	-0.50	-1.30
Asia	-0.11	-0.21	-1.06	-2.78*
Land Technology	-0.56	-1.18	-0.59	-1.77***
Information Tech.	-0.13	-0.23	0.37	0.79
<i>Wald test for Strength of Universality – Second Step</i>				
	χ^2 -statistic	<i>p</i> -value	χ^2 -statistic	<i>p</i> -value
	0.18	0.67	2.47***	0.12
<i>Other Variables</i>				
Independent Variables	Coefficient	<i>t</i> -statistic	Coefficient	<i>t</i> -statistic
Year of Data Collection	0.05	2.25*	0.04	2.35*
Linear Model	1.67	1.99*	0.92	2.22*
Tobit	0.71	0.94	0.98	2.15*
Education	0.53	1.22	0.38	1.24
Age	-0.82	-1.95**	-1.34	-4.48*
Experience	-0.80	-1.70**	-1.43	-4.42*
Outreach	-0.38	-1.02	-0.25	-0.86
Labor Constraint	0.32	0.86	0.59	2.14*
Land Quality	-0.37	-0.94	-0.01	-0.04
Land Tenure	-0.06	-0.15	-0.86	-2.84*
Other Social	0.24	0.61	0.09	0.31
Other Resource	-0.73	-1.65***	-0.65	-2.10*
R^2	.23		.15	

Note: Sample size is in hundreds of observations, *** is significant at the 15% level, ** is significant at the 10% level, and * is significant at the 5% level.

land technology to be negative and significant. Farm size is important in all locations and for all types of technology, though it seems to be less important in Asia relative to developed countries and less important for land technologies than for input technologies. These results are not surprising since Asian farms tend to be small and vary less in size than farms in developed nations. In addition, land on smaller farms may be used more intensively than larger farms. This is especially true in developing countries, where

many small farmers grow their own food in addition to cash crops, which make up their entire income. Because many of the land technologies enhance the productivity of the land, it is not surprising that small farmers would adopt.

Linear model is positively significant in both sets of results, and *Tobit* is significant in the MAD results, indicating that some of the variation in the z-scores for farm size may be caused by the study's methodology. Hence, farm size could play a slightly different role in adoption / nonadoption relative to the extent of adoption. The inclusion of socio-economic variables like *age*, *experience*, and *land tenure* may negatively impact the z-score for farm size. In as much as farm size can be seen as a proxy for income, the effect of including socio-economic variables can be explained in the same way it was explained for the education model.

Conclusions

The methodology used in previous meta-analyses has examined whether a relationship exists between two variables. The present study extends this methodology to examine the direction and strength of the relationship when one exists. Though sufficiently general to be applied in numerous settings, the methodology is used here to examine the direction and strength of the relationship between four factors (age, education, outreach, and farm size) and agricultural technology adoption. A factor that promotes or impedes technology adoption regardless of location or type of technology is called universal. Universal factors that promote technology adoption are positive universal, while those that impede adoption are negative universal. Strongly universal factors relate to technology in the same way regardless of location or type of technology, while the

magnitude of the relationship (not the direction) varies by location or type of technology for weakly universal factors.

The first step is to determine whether a factor is universal and if so, the direction of universality. In the case of agricultural technology adoption, the direction test proved to be fairly robust using OLS and MAD. Both estimation procedures indicate education and farm size are positive universal, and outreach is not universal. Only for age was there disagreement between OLS and MAD. Using $p = 0.15$ as a cutoff level, age is not universal using OLS ($p = 0.17$) and negative universal using MAD ($p = .05$). There is no disagreement in direction, only in significance level.

For factors that are shown to be universal in the first step, a strength test is performed. OLS results indicate education and farm size are strongly universal, while MAD results indicate weak universality. Smith and Huang suggest trusting MAD results over OLS results because of the weight OLS places on outliers. Evidence of weak universality for age, education, and farm size means technology promoters should not assume producers in different areas respond to all types of technology in the same way. In addition, outreach is not currently increasing adoption universally, though this does not mean it never will. For outreach to become a universal factor, outreach agents need to reevaluate their approaches. A first step towards outreach becoming a universal factor is for agents to better understand how factors impact adoption in different places and for different types of technologies. The results of this study indicate that outreach agents may want to target younger, more educated constituents with larger farms, realizing this may be less effective in Latin America and Asia than in other parts of the world. In

addition, similar analyses on other factors that may lead to adoption are necessary to enable outreach agents to refine their targeting strategies. Finally, to complete the adoption picture, the ramifications of weak universality on the adoption process need to be analyzed so outreach approaches can be further modified to have maximum impact in different situations.

In addition to helping outreach agents better target their constituents, the results of this study indicate the importance of looking at multiple studies to understand relationships between variables. While one might expect observed relationships to vary between studies done in different areas, on different populations, or in different time periods, the present study indicates this variation may be due to the choice of independent variables or the methodology used. Inclusion of socio-economic variables, for example, tends to lower the significance levels of education and farm size in technology adoption studies, while raising the significance levels of outreach. Linear models tend to increase the significance levels of age, outreach, and farm size. One might expect Tobit models to have different results because Tobit models examine a factor's influence on the extent of adoption as opposed to initial adoption, but Tobit models only seemed to make a difference in farm size (and only using MAD). It appears there is little difference in how a factor impacts initial adoption and how it impacts the extent of adoption. One could not see this result from examining only one or two studies, and yet the result simplifies the task of outreach agents, who can use the same targeting strategies on those who have not yet adopted and on those who have begun adopting.

Finally, the methodology developed in this study is sufficiently general to be applied to other areas of economics or any field concerned with systematic relationships between variables. In conjunction with relevant literature, researchers can use the definitions and tests developed in this chapter to determine whether the impact of one variable on another is positive or negative and what may cause the impact to vary.

CHAPTER IV

WHO BENEFITS FROM TECHNOLOGY ADOPTION? A CASE STUDY OF WHEAT PRODUCERS ADOPTING ENSO-BASED FORECASTS

The El Niño / Southern Oscillation (ENSO) phenomenon has been shown to affect climate patterns and agricultural production around the world. Though agricultural producers cannot control the climate, early forecasts of seasonal conditions may allow producers to make more efficient input decisions (Easterling and Stern; Hill et al. 1998). Scientific understanding of the coupled atmosphere / ocean system and associated ENSO phenomenon now allows forecasts to be issued with lead times of up to 13 months (Mason et al.; O'Lenic). Moreover, studies have shown the quality of these forecasts is improving (Wilks 2000; Livesey).

Most previous studies of climate information have used static models to show that society would benefit if all agricultural producers used climate forecasts in making production decisions (see Hill and Mjelde for a review of this literature). Climate information, however, can be viewed as a type of technology (Agrawala and Broad), which is generally adopted over time. Studies of technology adoption tend to be dynamic, examining economic effects from the time a technology is introduced until it is fully adopted. These studies are generally done *ex post*, however, when the distribution of benefits is known. No previous study has systematically examined the adoption of climate forecasts. This study combines the *ex ante* nature of climate studies with the dynamic nature of studies on technology adoption. The objective is to understand how the timing of adoption affects the benefits from adopting.

An international wheat trade model incorporating climate variability is used to simulate different scenarios when wheat producers in the U.S., Canada, and Australia adopt ENSO-based forecasts for use in production decisions. The model links forecast use to input usage, expected and actual yields, planted hectares, price, production, stocks, and trade through a system of economic equations. Baseline welfare measures are obtained under the assumption that no producers use climate forecasts. These baseline measures are compared to welfare measures when producers in the U.S., Australia, and / or Canada adopt climate forecasts either all at once or over time. Adoption levels and timing are varied across countries in different scenarios.

Brief Literature Review

Agrawala and Broad (p. 7) argue, “Seasonal forecasts, while not a piece of hardware, are certainly a knowledge product, and therefore they do fall within the purview of ‘technology.’” Information can be used or ignored by a producer, much as a technology can be adopted or not adopted. Therefore, literature on technology adoption combined with studies of climate forecast use provide the basis for understanding how ENSO-based forecasts may be adopted by decision-makers.

The S-shaped Adoption Curve

The most consistent result in the technology adoption literature is that the adoption path follows a sigmoid (s-shaped) curve over time (Feder, Just, and Zilberman; Stoneman 1981; Rogers and Stanfield). When first released, only a few agents adopt the technology. As information spreads, more agents become aware of the technology (Mansfield 1961) and its net benefits (Hoppe). More agents adopt, increasing the rate of

adoption. As time passes, the number of potential adopters decreases, eventually causing the rate of adoption to decrease. Ultimately, an adoption ceiling, or long-run equilibrium, is reached (Griliches). In many cases, the ceiling is reached before all agents have adopted the technology. For those who choose not to adopt, the technology may not be profitable, it may not be feasible, or a newer technology may have been adopted instead. Empirical studies support the s-shaped adoption pattern (Griliches; Mansfield 1961; Romeo). See Rogers and Stanfield; Feder and Umali; Marra, Pannell, and Ghadim for reviews of the literature on technology adoption.

Adoption of Climate Forecast Information

The literature on climate forecast use tends to ignore the ideas that adoption takes place over time and that some producers may never adopt. One reason for ignoring time is that improved climate forecasts are relatively new. Only the earliest adopters are using the information. There has not been sufficient diffusion to estimate s-shaped adoption curves or to predict how many producers will ultimately adopt. Previous adoption literature and economic theory show that technology will only be used if it is profitable. Many studies, therefore, concentrate on calculating the economic value of climate forecast use (e.g. Bowman, McKeon, and White; Messina, Hansen, and Hall; Hammer, Holzworth, and Stone; Solow et al.; Hill et al. 2004; Costello, Adams, and Polasky; Adams et al.). Though nearly all these studies report positive values, it is important to note that benefits do not accrue to everyone (Hill and Mjelde; Peterson and Fraser; Lamb.). This is not surprising since the effect of ENSO events varies by location.

Several studies examine how climate forecast use affects world trade. Sumner, Hallstrom, and Lee show that welfare effects vary depending on a country's trade policies and size, responses by other countries, and demand. Chen and McCarl find that welfare increases when ENSO forecasts are used in regional world agricultural production. They report that U.S. consumers and foreign trading countries gain while U.S. producers lose. Hill et al. (2004) find that the use of climate forecasts by wheat producers leads to a drop in U.S. production, which leads to an increase in price and an increase in producer surplus.

Though climate information has been shown to have value, there are impediments to adoption (Glantz). Decision-makers may not know the information is available (Changnon, Sonka, and Hofing), the information may come too late (Washington and Downing), or it may not be in a usable form (Goddard et al.; Callahan, Miles, and Fluharty). Even if the information is received in a timely manner and understood, it is often difficult to integrate into production decisions, especially when complex corporate structures are involved (Changnon, Sonka, and Hofing; Goddard et al.; Pulwarty and Redmond; Changnon, Changnon, and Changnon). Furthermore, distrust, misunderstanding, and prior beliefs can hinder forecast use (Changnon, Sonka, and Hofing; Letson et al.; Nicholls 1999; Agrawala and Broad), as can resource constraints (Agrawala and Broad).

In addition, climate forecasts may have specificity issues (Hill and Mjelde). Regional forecasts may not be accurate for the producer's land. Though the scientific and economic aspects of climate forecasting are still emerging, and impediments to use

remain, there is substantial evidence that climate forecast use in agricultural production decisions will affect global economic welfare. Knowing how the timing of adoption affects the benefits from adopting will help producers, policy-makers, and society make better decisions.

International Wheat Trade Model

A dynamic, stochastic wheat trade model, which assumes a competitive trade environment, provides the basis for this study (Hill et al. 2004). An overview of the model can be seen in figure 4.1. The model includes equations for production, demand, stocks, and exports for three major wheat-producing countries, U.S., Canada, and Australia. Other wheat-producing countries, Argentina, Europe, and China are modeled in less detail. Argentina represents a small percentage of world wheat trade, Europe is relatively unaffected by ENSO, and China is nearly impossible to model in a free trade environment using historical data. All other countries are aggregated into a Rest-of-World (ROW) category.

World wheat trade is simulated over a 20-year horizon using random starting values (a feature added to Hill et al.'s model). Technology, population, income, transportation costs, and input prices are fixed to isolate potential effects of producers' use of seasonal climate forecasts. Baseline simulations assume producers do not use ENSO-based climate forecasts; instead they base decisions on historical distributions of climate conditions. Simulations assuming wheat producers use ENSO-based forecasts are compared to the baseline to evaluate the effect of ENSO-based climate forecasts on

producer surplus. The five phases of the Southern Oscillation Index (SOI), a measure of the atmospheric pressure differences between the island of Tahiti and Darwin, Australia

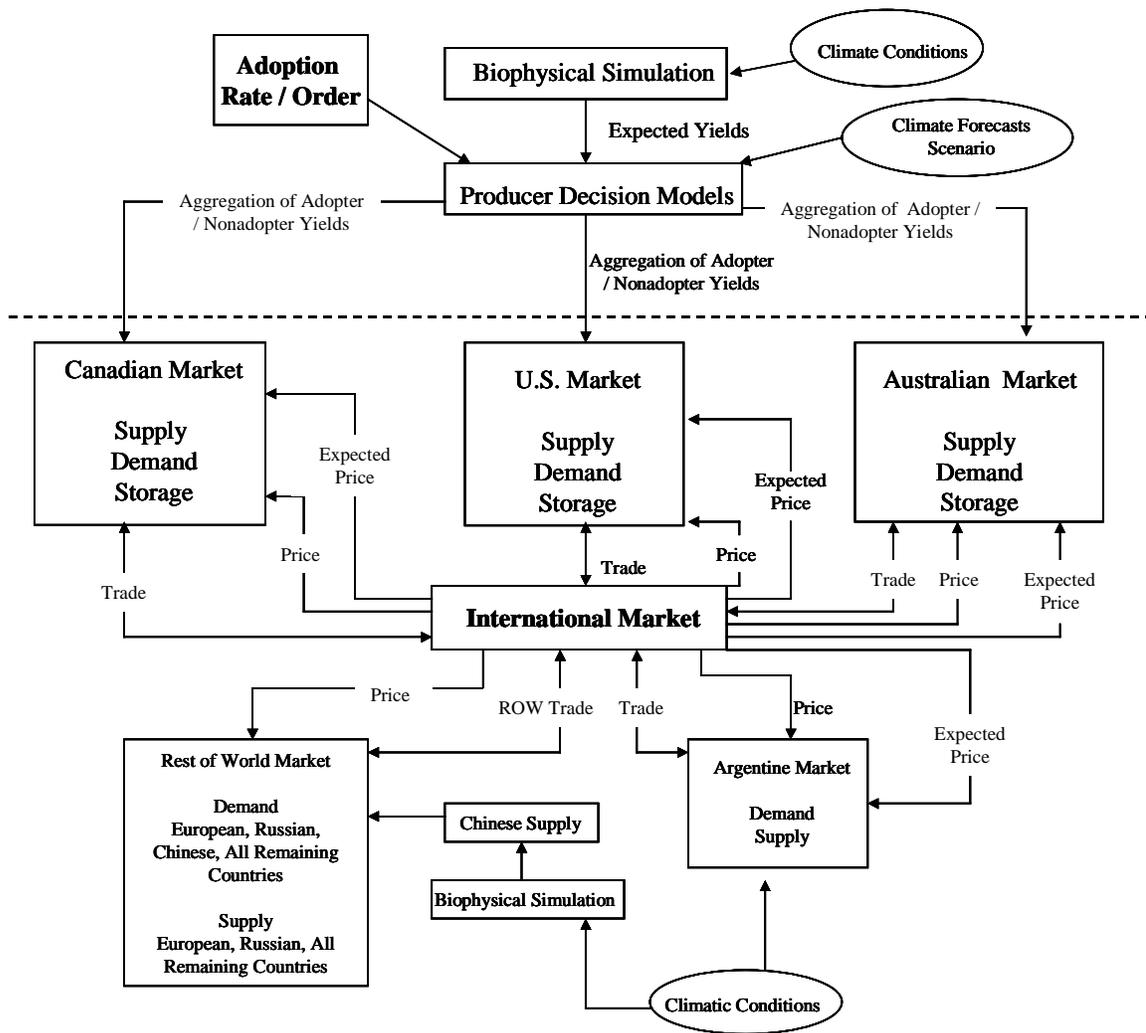


Figure 4.1. Overview of simulated wheat trade model

(Stone and Auliciems), are used to represent ENSO conditions. Near normal conditions are represented by Phase 5. Phases 1 and 3 are related to El Niño conditions (warm events), whereas phases 2 and 4 are related to La Niña conditions (cold events) (Stone and Auliciems). Generally, opposite conditions (warm / dry or cold / wet) are experienced in Australia and regions of North America for a given SOI phase.

Production

Because ENSO-based seasonal forecasts are a recent development, standard econometric methods cannot be used to estimate aggregate production. Therefore, a proxy for producers' behavior must be used. Biophysical simulation models combined with field-level decision models are used to obtain yields for representative fields throughout the U.S., Canada, and Australia under a range of management practices, site-specific characteristics, climatic conditions, and expected prices (figure 4.1). Producers respond to ENSO-based climate forecasts by changing planting dates and nitrogen application rates and, in the case of Australia, wheat variety.

The CERES-Wheat Model (Godwin et al.) is used to simulate wheat yields in North America, whereas I-Wheat in the APSIM model is used to simulate Australian wheat yields (Meinke et al.). The models require daily weather, soil, and variety-specific genetic inputs. Ten sites in the major winter wheat producing area in the U.S. are modeled. Twelve sites are modeled to represent major Canadian and U.S. spring wheat growing areas. In Australia, nine sites that form an arc through the wheat belt are used to simulate wheat yields.

Daily weather data from 1910 to 1995 are used to simulate yields for the North American sites, while weather data from 1916 to 1993 are used in Australia. The classification of the season is based on the planting dates in each country. For Canada, Australia, and spring wheat areas in the U.S., the April-May SOI phase is used. For winter wheat in the U.S., the August-September SOI phase is used.

Yield equations are obtained by regressing simulated national wheat class yields on expected prices and SOI phases to obtain:

$$(4.1) \quad Y_{i,t}^{v,c} = E_{t-1}(P_{i,t})^{\beta_{0,i}^c} e^{\sum_{k=1}^5 \beta_{k,i}^c \alpha_k} \varepsilon_{i,t}^{v,c}$$

where

$Y_{i,t}^{v,c}$ is the hectare-weighted yield, for country i , year t , and wheat class v ,

$c = 1$ indicates adopters of climate forecasts and $c = 0$ indicates use of climatological (historical) climate information,

$E_{t-1}(P_{i,t})$ is the expected price in year $t-1$ for production associated with year t ,

e is the exponential operator,

α_k are binary variables for the five SOI phases, denoted by k ,

$\beta_{k,i}^c$ are estimated coefficients, and

$\varepsilon_{i,t}^{v,c}$ is a random error term.

For each country and wheat class (hard red spring, hard red winter, soft red winter, soft white, Canadian western red spring, and Australian standard white), two yield equations

are included - one for producers using climate forecasts ($c=1$) and one for producers basing their production decisions on historical distributions of climate variables ($c=0$).

The number of hectares planted to wheat is given by:

$$(4.2) \quad H_{i,t}^v = \lambda_{i,v} E_{t-1}(P_{i,t})^\eta$$

where H is hectares, v and t are wheat class and year, λ is a constant term, η represents the hectare price elasticity, and the expected price is the same value used in the yield equation. Country-specific aggregate production, $S_{i,t}^v$, for each wheat class is:

$$(4.3) \quad S_{i,t}^v = H_{i,t}^v (Y_{i,t}^{v,c}).$$

Hill et al. (2001) provide further details on the methodology used to obtain aggregate country-level production that incorporates climate forecast information.

Demand

Following Maaki, Tweeten, and Miranda, country level, per-capita demand equations are:

$$(4.4) \quad D_{i,t} = \phi_{1,i} (P_{i,t}^c)^{\phi_{2,i}} (I_{i,t})^{\phi_{3,i}}$$

where $D_{i,t}$ represents per-capita demand in country i , $\phi_{1,i}$ is a constant term for country i , $P_{i,t}^c$ is price, $\phi_{2,i}$ is the demand price elasticity in country i , I is per-capita income, and $\phi_{3,i}$ is the income elasticity in country i .

Prices and Storage

Producers are assumed to use quasi-rational price expectations, which means producers efficiently use available information such as seasonal forecasts to anticipate price adjustments resulting from changes in production. Quasi-rational price expectations do

not require decision-makers to be aware of the structural parameters for the complete economic system, as is the case under rational price expectations (Nerlove and Bessler; Burton and Love). The price expectation equation for U.S. wheat producers enters the model as follows:

$$(4.5) \quad E_t(P_{US,t+1}^c) = \alpha_0 + \alpha_1 P_{US,t} + \alpha_2 TP_{t+1}^c + \alpha_3 TE_t$$

where $E_t(P_{US,t+1}^c)$ is the expected price in year t for year $t+1$, the α 's are estimated coefficients from a two-stage least squares price equation, TP_{t+1}^c is expected total production in the U.S., Canada, and Australia in year $t+1$, c indicates the use of climate forecasts, and TE_t is the sum of exports for the U.S., Canada, and Australia in year t . Both climate forecasts and expected price affect expected production. At the same time, expected production impacts expected price. The model solves expected price and expected production for each year simultaneously. Both expected production and expected price are, therefore, functions of the forecasted climate conditions.

Stock equations are estimated functions of the discounted expected price in year t for $t+1$, the actual price in t , and beginning stocks.

$$(4.6) \quad Z_{i,t} = \psi_{0,i} + \psi_{1,i} Z_{i,t-1} + \psi_{2,i} \{ \delta_i (E_t(P_{i,t+1}^c) - P_{i,t}^c) \}$$

where $Z_{i,t}$ represents the stock in year t for country i , ψ 's are estimated parameters, and δ_i represents the discount rate.

Price in the U.S. is a function of stocks and expected price for year $t+1$ in year t . Assuming efficient arbitrage, prices in Canada, Australia, Argentina, and ROW are linked to the U.S. price through transportation costs and exchange rates. To ensure

market-clearing, the sum of each country's imports, supply, and beginning stocks equals the sum of its demand, ending stocks, and exports. To close the model, U.S. exports are set equal to ROW imports minus exports by Argentina, Australia, Canada, and Europe.

Unique to this model is the use of ENSO-based climate forecasts by producers to alter their production decisions. The adoption of climate forecasts by producers is manifested in the trade model through the number of hectares planted and changes in input usage, which causes changes in yields per hectare. Both input usage and planted hectareage depend on the expected price, which is a function of the expected yield, which depends on the forecasted climate.

Model Verification

Production and price from the model are compared with historical data to verify the model. Production in the U.S. and Canada are within 10% of historical averages, and Australia is within 20%. The greater discrepancy in Australia is due to the exclusion of hard prime wheat in the model. Prices obtained from the trade model for the U.S. and Australia are within 3% of historical prices, while the discrepancy for Canada is 18%. The larger difference for Canada is likely due to recent depreciation of the Canadian dollar, while the model simulates 1997 conditions. Price drives the model, so the similarity between the model's prices and historical values is an indication that the model approximates reality. Finally, estimated own-price elasticities of supply are close to consensus estimates, as are estimated own-price elasticities of demand.

Modeling Adoption

For most technologies, the adoption path can be divided into three phases that mirror the product life cycle. The first phase corresponds to the s-shape. A technology is introduced and then adopted over time until an adoption ceiling is reached. The first phase is dynamic in that the number of adopters is changing, as is the distribution of benefits. Most producers do not adopt new technologies the moment they are released. It takes time for information to spread, risk to be assessed, and the adoption decision to be made. Adoption in the second phase is more static. The adoption ceiling has been reached, and there is an equilibrium number of adopters and nonadopters. Adopters have no incentive to un-adopt, while nonadopters have no incentive to adopt. The third phase begins when a substitute technology is introduced, and those who have adopted the older technology begin switching to the newer, substitute technology. The cycle begins for the new technology, while the number of people using the older technology decreases. Because ENSO-based climate forecasts are relatively new, this study focuses on the first two phases.

Examining both phases of adoption allows us to determine how adoption decisions in one area affect the rest of the world. Hill et al.'s (2004) model only allows 100% adoption and, therefore, must be modified to allow some producers to adopt while others do not. Adoption is added to the model by modifying the production equations in the U.S., Canada, and Australia to reflect the percentage of producers using ENSO-based climate forecasts to make production decisions. Because producers in different countries are likely to adopt climate forecasts at different rates, the trade model allows the rate of

adoption to vary by country. A logistic function is used to represent an s-shaped adoption path over time in each country. The percentage of producers adopting climate forecasts in each scenario is given by:

$$(4.7) \quad d_{i,t} = \frac{e^{(a_i + b_i t)}}{1 + (e^{a_i + b_i t})}$$

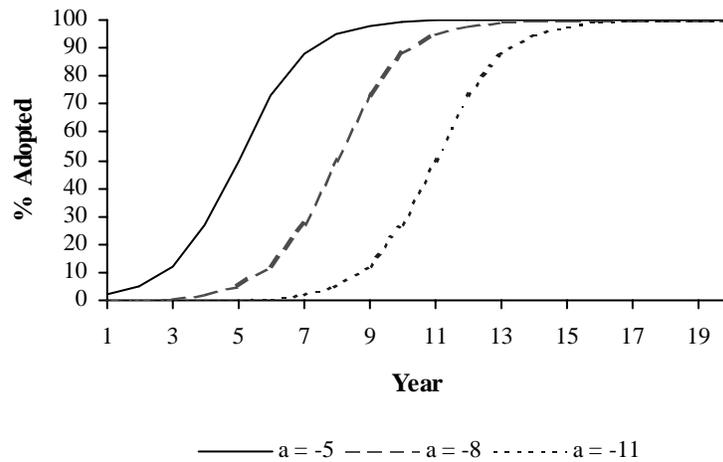
where a_i and b_i are country specific constants and t , which ranges from 1 to 20, represents the year since the beginning of the simulation. Obviously, the percentage of nonadopters is given by $1 - d_{i,t}$. By incorporating an adoption function for each country, producers in the U.S., Canada, and Australia can adopt at different rates. Aggregate production for each country becomes:

$$(4.8) \quad S_{i,t}^v = H_{i,t}^v (d_{i,t} Y_{i,t}^{v,1} + (1 - d_{i,t}) Y_{i,t}^{v,0})$$

Because there is neither data to conduct an *ex post* analysis nor empirical studies that provide explicit values for a_i and b_i , arbitrary numbers are used. The choice of numbers does not appear to affect the results, as several sets of numbers were tried.

First phase of adoption. The first phase of adoption is examined through two sets of simulations that focus on adoption over time. These simulations determine the percentage of adopters at the adoption ceiling, as well as how the order and rate of adoption affects the distribution of benefits and losses to producers. First, three different intercepts (a_i 's) are used with a constant b . Varied intercepts allow producers in different countries to begin adopting in different years, though once adoption begins, the rate of adoption is the same in all countries. The three different adoption paths are

(a) Same Adoption Rates But Different Starting Dates ($b = 1$)



(b) Same Starting Date But Different Adoption Rates ($a = -6$)

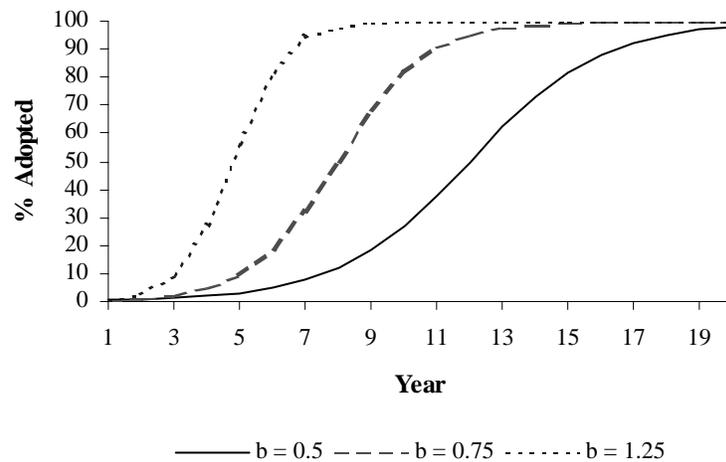


Figure 4.2. Assumed adoption paths, where d_t is the logistic function

$$d_t = \frac{e^{(a+bt)}}{1 + (e^{a+bt})}$$

shown in figure 4.2, panel a. Values for a are -5, -8, -11 with b held constant at 1.

Values for a closer to 0 correspond to earlier adoption.

Second, producers in all three countries begin adopting in year 1, but adoption occurs at different rates (figure 4.2, panel b). Here, a is held constant at -6, and b is allowed to vary. The b 's are set equal to 1.25, 0.75, and 0.5, where larger numbers indicate faster adoption.

Second phase of adoption. The second phase of adoption is addressed with simulations that examine the distribution of benefits and losses to producers at the adoption ceiling. Here, it is assumed all producers in a given country either adopt or do not adopt climate forecasts at the beginning of the 20-year horizon. Once this decision is made, it is irreversible. For example, in one scenario all U.S. producers adopt, but no producers in Canada or Australia adopt. In this case, $d_{i,t}$ equals one for all U.S. producers and zero for producers in Canada and Australia for all years. Extreme, no adoption / 100% adoption scenarios are examined for all countries, as are less extreme, partial adoption scenarios.

Results and Discussion

The discussion is limited to producer surplus for two reasons. First, most of the welfare change in the trade model accrues to producers. Second, the focus on producer surplus keeps the presentation manageable. Hill et al. (2004) discuss changes in other economic measures when all wheat producers simultaneously adopt climate forecasts in their production decisions.

Phase One - Adoption Over Time

For the scenarios examining adoption over time, three producer surplus paths are presented for each country (figures 4.3 – 4.6). The vertical axes represent producer surplus per hectare, and the horizontal axes indicates the year. The three paths correspond to no adoption, adopters, and nonadopters. No adoption producer surplus is the baseline case, where all producers in all countries make production decisions based on historical distributions of climate events and not ENSO-based climate forecasts. Producer surplus for adopters (nonadopters) refers to the surplus of producers in the country at hand who have adopted (not adopted), given the assumed adoption path in all three countries. In the following discussion, gains and losses refer to changes in per-hectare producer surplus for adopters (nonadopters) relative to producer surplus under the no adoption assumption.

In all cases, the earliest adopters realize the largest gains. Gains eventually decline as more producers adopt. This decline begins in years 6 - 13 depending on the assumed adoption paths. In addition, there is a point (between 60 and 95 percent adoption) when nonadopters begin to gain more than adopters. Nonadopter gains continue to increase until all agents have adopted, at which point there are no nonadopters. Economic theory indicates, however, that once the benefits to adoption equal the benefits to nonadoption, there is no longer an incentive to adopt, and the adoption ceiling is reached. In figures 4.3 - 4.6, the adoption ceiling is given by the crossing of the adopter and nonadopter producer surplus paths.

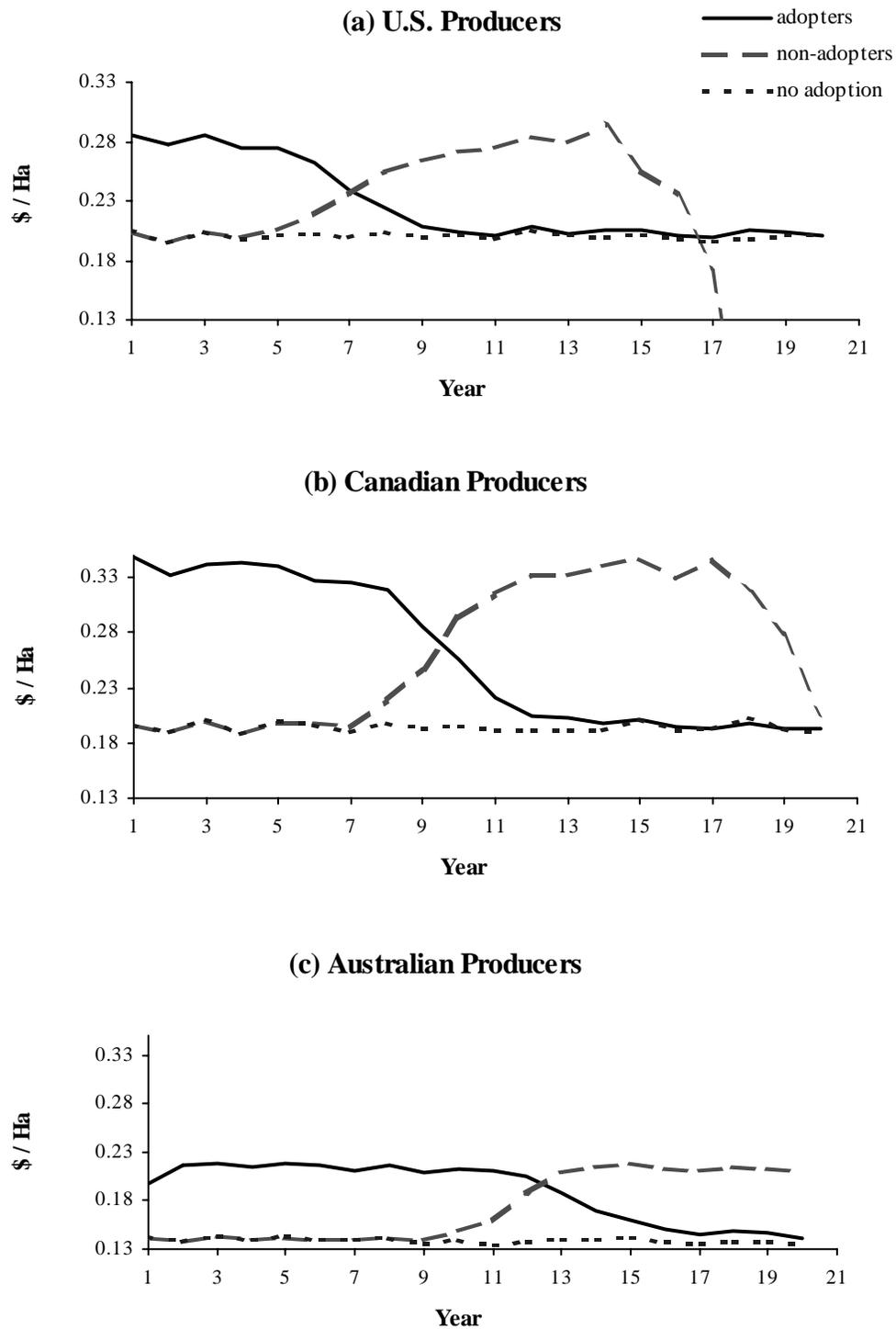


Figure 4.3. Producer surplus over time when U.S. starts adopting first, Canada starts adoption second, and Australia starts adoption third (figure 4.2, panel a)

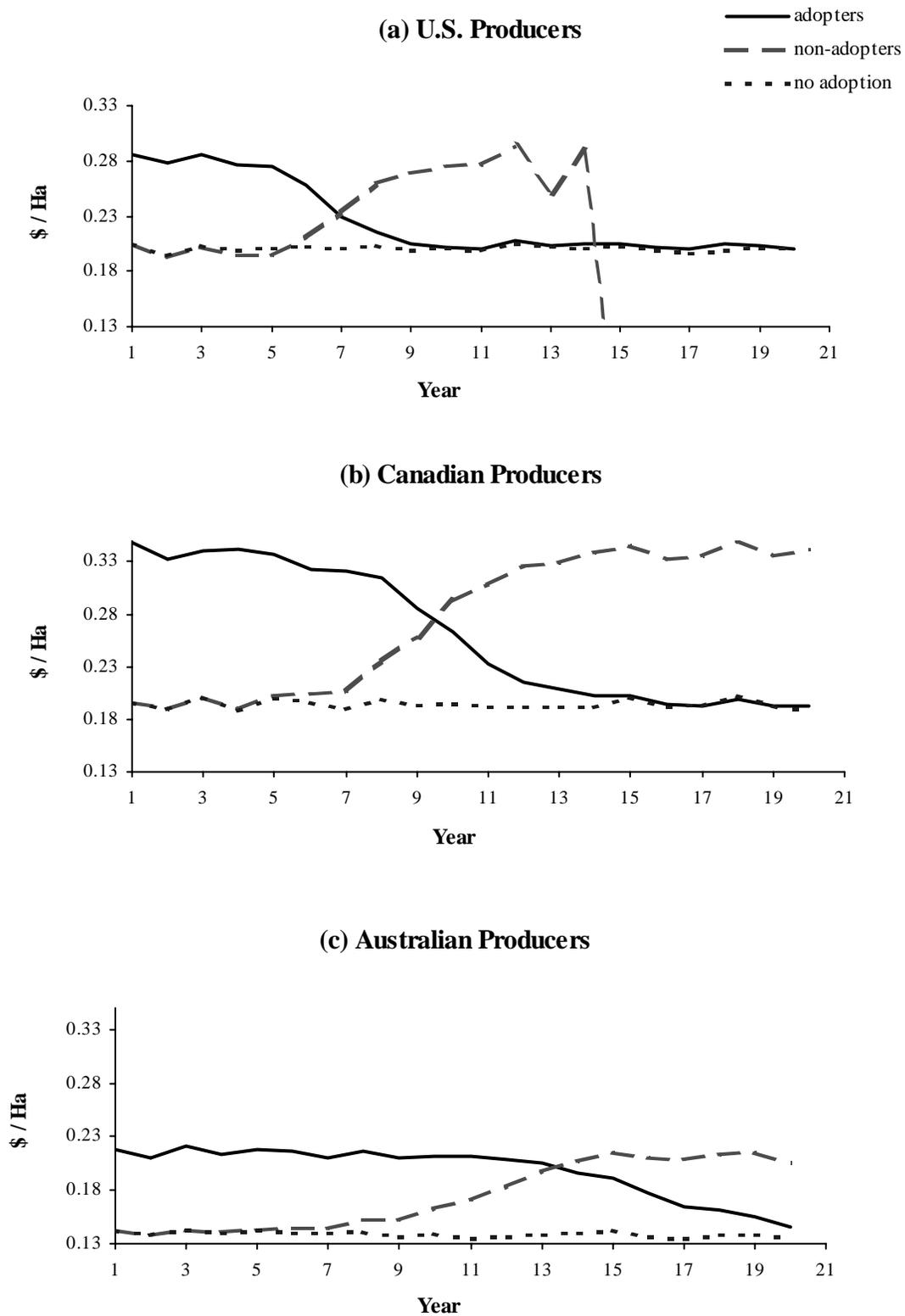


Figure 4.4. Producer surplus over time when the U.S. adopts fastest, Canada adopts second fastest, and Australia adopts slowest (figure 4.2, panel b)

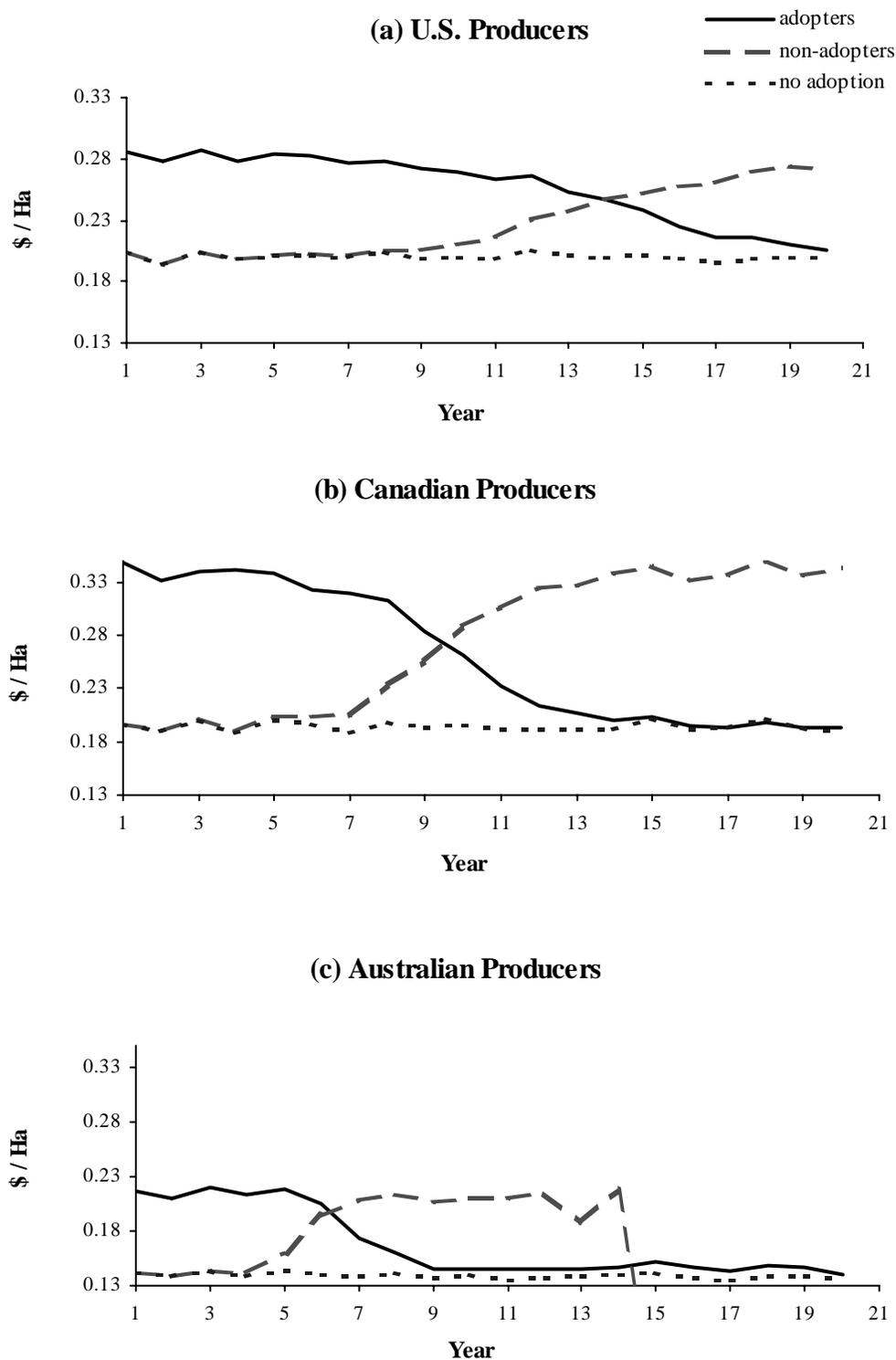


Figure 4.5. Producer surplus over time when Australia adopts fastest, Canada adopts second fastest, and U.S. adopts slowest (figure 4.2, panel b)

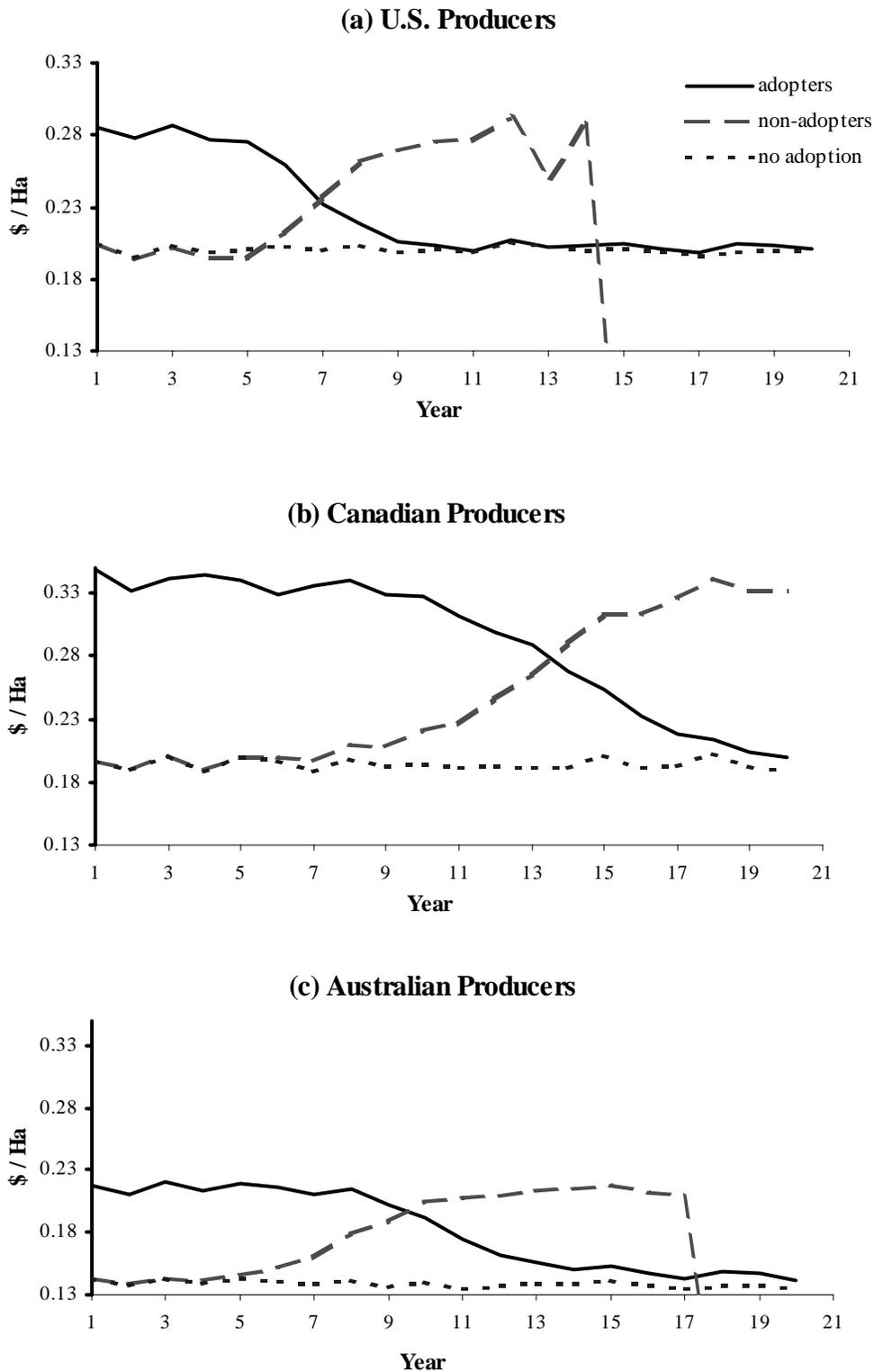


Figure 4.6. Producer surplus over time when U.S. adopts fastest, Australia adopts second fastest, and Canada adopts slowest (figure 4.2, panel b)

The two per-hectare paths cross because producer surplus changes at a different rate than hectares. As more producers use climate forecasts, adopters' total producer surplus increases more slowly than the number of hectares they plant. The ratio is, therefore, decreasing. In a similar fashion, producer surplus for nonadopters decreases more slowly than the number of hectares decreases. The ratio, therefore, increases. The phenomenon can be explained by examining the supply curves. Both adopters' and nonadopters' supplies are upward-sloping, nonlinear curves. At low levels of adoption, the supply curve for adopters is steeper than it is at higher levels of adoption. Adopters' producer surplus is increasing as more producers adopt, but it is not increasing as fast as the number of hectares. The gain to each additional hectare is progressively smaller. The argument is reversed to explain why nonadopters experience larger gains as their numbers dwindle.

In figure 4.3, the rate of adoption is the same for all countries, though the U.S. begins adopting first, followed by Canada and then Australia (see figure 4.2, panel a). In all three countries, gains for adopters begin high and remain fairly steady until year 6 in the U.S., year 8 in Canada, and year 12 in Australia. Gains for adopters then start to decrease. The adoption ceiling is reached in year 7, 10, and 13 in the U.S., Canada, and Australia, respectively. In each country, the ceiling occurs when approximately 88% of the producers have adopted. Although not presented graphically, producer surplus takes a similar path when the order of adoption for the three countries is changed. For example, when U.S. producers begin adopting first, followed by Australian producers and then Canadian producers, the adoption ceilings occur in years 7, 9, and 12 with

adoption ceilings at 88%, 73%, and 73%. Again, the earliest adopters in each country gain the most.

In figure 4.4, producers in all three countries begin adopting at the same time but at different rates (see figure 4.2, panel b). U.S. producers adopt the fastest, followed by Canadian producers, and then Australian producers. The pattern of benefits is similar to figure 4.3. Gains are steady and then dip just before the adoption ceiling, which occurs in year 7 in the U.S. when 94% of producers have adopted, in year 10 in Canada at 81% adoption, and in year 14 in Australia at 73% adoption. In figure 4.5, the adoption paths for the U.S. and Australia are switched. The U.S. now adopts the slowest, resulting in an elongated benefit pattern. Australia adopts the fastest, causing the benefit pattern to be shortened. The general shape for each country remains the same. The ceiling is reached in year 14 in the U.S. at 73% adoption, in year 10 for Canada at 81% adoption, and in year 6 for Australia at 81% adoption. Finally, figure 4.6 contains the producer surplus paths when U.S. producers adopt the fastest, followed by Australian producers, and then Canadian producers. U.S. producers reach the adoption ceiling in year 7 with 94% adopting, Australian producers reach the ceiling in year 9 with 68% adopting, and Canadian producers reach the ceiling in year 13 with 62% adopting. The slower a country adopts relative to the other countries, the lower the adoption ceiling tends to be.

Altering the order and rate of adoption changes the timing of benefits but not the general pattern. In all cases, the earliest adopters gain the most, indicating that order matters. The adoption ceiling is below 100% in every country for every scenario, and nonadopters gain relative to no-adoption at the ceiling. The impact of adoption

decisions goes beyond the individual decision maker. The welfare of each producer is affected by how many other producers have already adopted and in which countries they reside.

Phase Two - Adoption Ceiling Reached

To obtain a better understanding of the adoption process, three sets of results are presented, which assume various adoption ceilings have been reached. First, all combinations of the extreme cases of 0% adoption and 100% adoption are presented. Next, results are presented based on partial adoption in one country and 100% adoption in the other two. The last set of results is based on approximate adoption ceiling levels indicated in the section on Phase One - Adoption Over Time.

All or nothing adoption. Given that adoption is not likely to reach 100%, the extreme cases that every producer in a country adopts or nobody adopts are likely to underestimate gains from adopting. However, examination of all possible combinations of 0 / 100% adoption aids in the understanding of how adoption in one country impacts producers in other countries. With three countries, there are seven all-or-nothing adoption possibilities (table 4.1). The results indicate that adoption is the best choice for producers in all countries, especially if producers in other countries are adopting.

When everybody adopts climate forecasts, producers in all three countries benefit. Australia's climate is affected more by ENSO than the U.S. or Canadian climates, so it is not surprising that Australian producers, with an average increase in surplus of 7.53%, gain the most by using ENSO-based forecasts. U.S. producers' welfare increases on average by 2.22%, while producers in Canada gain 1.33%.

Table 4.1. Mean Percentage Changes in Present Value Producer Surplus Over 20 Years for 1000 Simulations Assuming No Adoption or 100% Adoption

	<u>Australia Adopts</u>			<u>Canada Adopts</u>			<u>U.S. Adopts</u>		
	Aus	Can	U.S.	Aus	Can	U.S.	Aus	Can	U.S.
Mean %	6.29	-0.15	0.06	0.06	0.59	-0.28	1.01	1.32	2.83
Std. Dev.	8.39	1.64	1.47	10.00	10.02	10.24	5.14	5.53	2.00
	<u>Canada & Australia Adopt</u>			<u>U.S. & Australia Adopt</u>			<u>U.S. & Canada Adopt</u>		
	Aus	Can	U.S.	Aus	Can	U.S.	Aus	Can	U.S.
Mean %	6.56	0.52	-0.34	7.19	1.20	2.76	1.13	1.37	2.29
Std. Dev.	13.65	10.28	10.27	9.85	5.93	2.53	11.52	11.36	10.61
	<u>U.S., Canada, & Australia Adopt</u>								
	Aus	Can	U.S.						
Mean %	7.53	1.33	2.22						
Std. Dev.	14.80	11.66	10.66						

Even if producers in the U.S. and / or Canada do not adopt climate forecasts, Australia has the most to gain by adopting. If Australian producers adopt, their minimum average change in producer surplus is 6.29%. When Canadian producers also adopt, Australia's average producer surplus gains increase to 6.56%. When U.S. and Australian producers adopt, Australian producer surplus increases by 7.19%. Even if Australian producers do not adopt, they gain if either Canadian or U.S. producers adopt. Canadian adoption increases Australia's average producer surplus by a mere 0.06%, but U.S. adoption leads to an average gain of 1.01% for Australia's producers. When Canada and the U.S. both adopt, Australia gains 1.13%. In addition to the more efficient use of inputs by Australian producers, Australian gains are also partially explained as follows: when U.S. producers use climate forecasts, U.S. production tends to decrease relative to production levels when the forecasts are not used. The relative decrease in U.S. production is accompanied by a slight increase in the world price, which is not

surprising, given the magnitude of U.S. production relative to production in the rest of the world.

Producer surplus gains in Canada are driven by U.S. adoption. When Canadian producers adopt alone, they gain an average 0.59%. When only the U.S. adopts, producers in Canada gain an average of 1.32%. This is increased to 1.37% if Canada also adopts. The reasons for these gains are the same as for Australia. By adopting, Canadian producers use their inputs more efficiently. U.S. adoption leads to an increase in the world price, which benefits Canadian producers. Australian adoption, on the other hand, hurts Canadian producers. When Australia adopts alone, Canadian producers lose an average 0.15%. This is because production in Australia tends to increase with adoption, which exerts a slight downward pressure on the world price.

Given the above results, it is not surprising that U.S. producer surplus decreases when either Canada or Australia adopts. U.S. producers gain the most when they alone adopt, (2.83%), and lose (-0.34%) when they alone do not adopt. It is interesting that despite declines in production, the U.S. can increase producer surplus by adopting, especially if others are adopting. Increases in producer surplus accompany production declines because U.S. producers use their inputs more efficiently when they adopt climate forecasts (Hill et al. 2002).

The above results are based on average percent changes in producer surplus over the 20-year simulation horizon. Probability distributions are given in figure 4.7 for selected scenarios. The horizontal axes represent percent gains or losses relative to the baseline. Though the positive means indicate overall gains to adoption, the variation

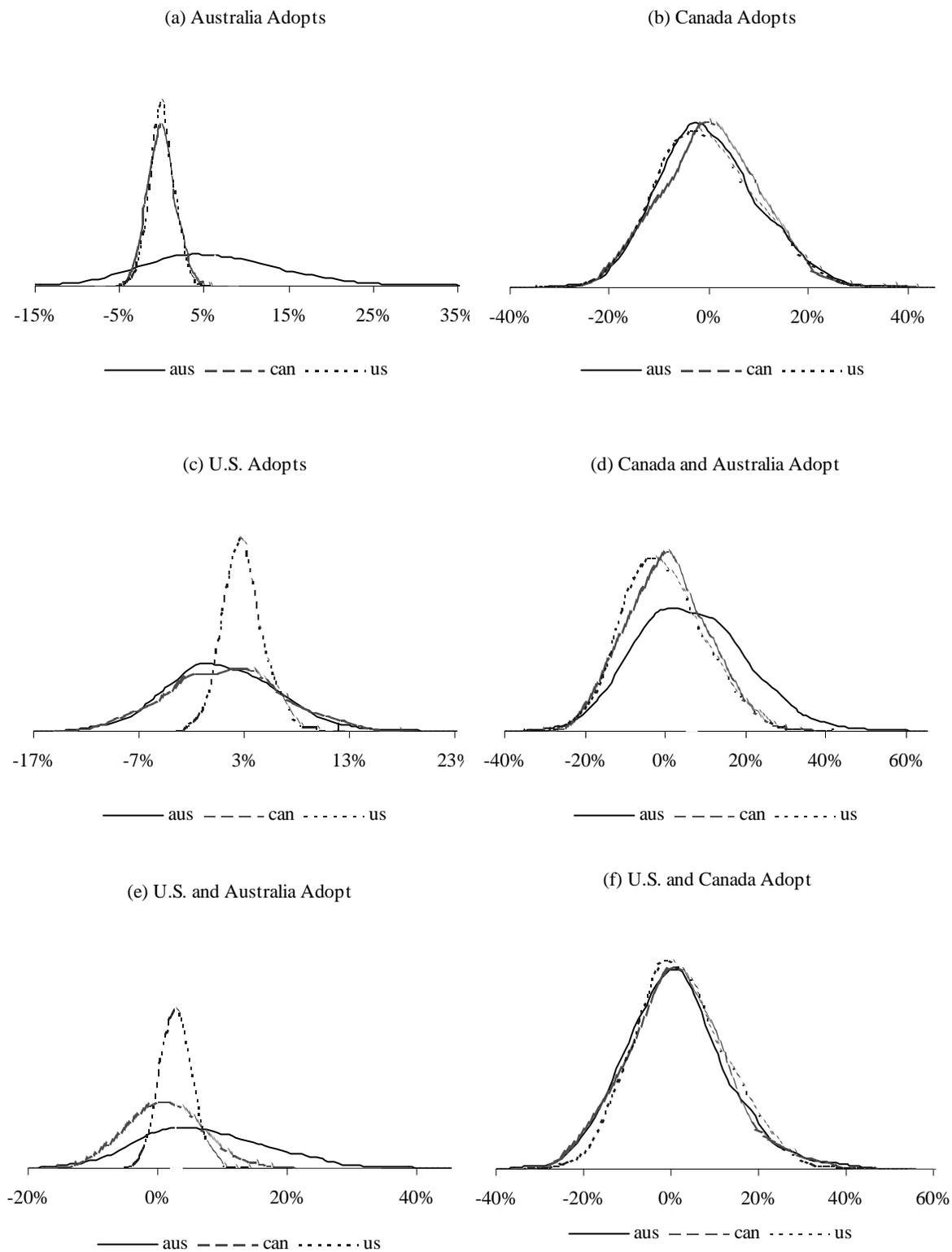


Figure 4.7. Probability distributions of average changes in present value producer surplus over 20 years and 1000 simulations under different adoption scenarios

shows adopters may lose in some years relative to the baseline. It is not surprising that producer surplus changes vary the most in Australia and the least in the U.S. As mentioned, ENSO affects Australia more than the U.S. When Australia adopts alone (figure 4.7, panel a), there is a 25% chance adoption will lead Australian producers to gain more than 11.15%, and another 25% chance that adoption will cause them to gain less than 0.65% relative to if they had not adopted. On the other hand, when the U.S. adopts alone (figure 4.7, panel c), there is a 25% chance U.S. producers will gain more than 3.99%, and a 25% chance they will gain less than 1.49% relative to nonadoption.

Partial adoption in one country. Various scenarios are examined where all producers in two countries adopt, while only a fraction of producers in the third country adopt. The results, shown in figure 4.8, further illustrate how the percentage of adopters in one's own country and abroad affects producer surplus. The vertical axes in figure 4.8 are the average percentage changes in producer surplus between each scenario and the (no adoption) baseline scenario. The horizontal axes are the fraction of producers in the partially adopting country who have adopted. It can be seen that gains in producer surplus are the highest in the partially adopting country when approximately 50% of the producers have adopted. Producer surplus gains in the countries with 100% adoption are positive and fall within the ranges of the all or nothing scenarios given in table 4.1. Again, we find 100% adoption to be sub-optimal. One country partially adopting and two countries with 100% adoption (figure 4.8) is not a stable equilibrium because there are gains to unadopting in the two countries with 100% adoption.

Partial adoption in three countries. Because the adoption over time results indicate adoption ceilings between 62% and 94% depending on the order and rate of adoption, a scenario when 80% of producers in each country adopt climate forecasts is simulated. The average U.S. gain in producer surplus is 16.82%, while in Canada, the average gain is 29.54%, and in Australia, 33.64%. These results show substantial gains to adopting climate forecasts and illustrate once again the interconnectedness of the adoption decision. The gains are lower than the maximum gains to partial adopters in figure 4.8 but higher than the gains in the two countries with 100% adoption. These gains are also higher than under the assumption of 100% adoption in all three countries. Thus, 100% adoption is not optimal. It is interesting to note that at the ceiling, both adopters and nonadopters benefit. When assessing potential benefits of a new technology, it is important to correctly predict the adoption ceiling. Assuming 100% adoption may lead to underestimation of benefits. In this case, assuming 100% adoption results in U.S. producers gaining more than Canadian producers, while examining partial adoption shows Canadians gaining more than their U.S. counterparts. In all cases, Australian wheat producers have the most to gain by adopting improved climate forecasts.

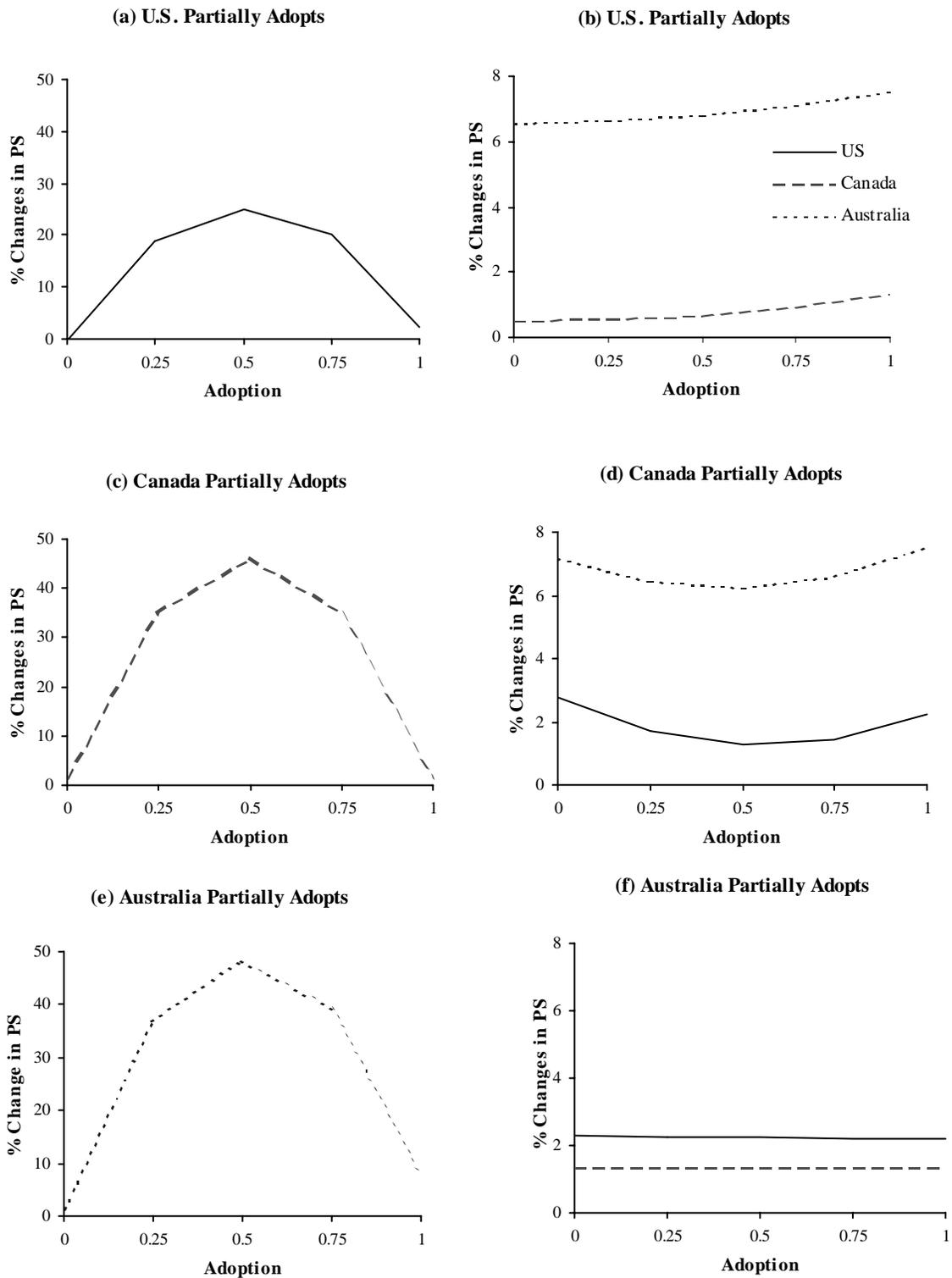


Figure 4.8. Partial adoption in one country and 100% adoption in two countries for 20 years and 1000 simulations

Conclusions

This is the first study to systematically examine technology adoption in multiple countries *ex ante* in order to predict how the timing of adoption will affect the benefits of adoption. This is also the first time the benefits of partially adopting ENSO-based climate forecasts have been studied in different countries. Results are consistent over all scenarios. Regardless of who adopts first or how fast they adopt, the pattern of benefits does not change. Altering the rate or order of adoption only changes the timing of benefits, not the pattern. In all cases, the earliest adopters gain the most. Over time as more producers adopt, the benefits decline until they equal the benefits of nonadoption. At this adoption ceiling, which is below 100% adoption, the benefits are higher than if nobody had adopted. In other words, nonadopters benefit from the adoption of others.

A further finding is that the slower a country adopts, the lower the adoption ceiling tends to be. Depending on the order of adoption, the ceiling is likely to fall between 60% and 95% adoption in each country. This result is important for agencies pushing adoption. Adoption decisions do not happen in a vacuum. Each producer's decision affects the welfare of all other producers. The benefits of adoption depend on how many others have adopted and where these adopters are located. While agencies can help their constituents be among the first to adopt and thus the greatest beneficiaries, they need to be aware that not everybody should adopt climate forecasts. The benefits to adoption can be estimated, and when they equal the benefits to nonadoption, the ceiling has been reached, and the agency can turn its attention elsewhere.

CHAPTER V

CONCLUSIONS

Given technology's importance in numerous fields of economics, understanding the process of technology adoption is imperative, especially for those pushing adoption to achieve a cleaner environment, more efficient use of natural resources, economic growth, development, or some other goal. Specifically, it is important to understand who is likely to adopt and what the benefits are for a given a location, type of technology, and current level of adoption. Previous studies have focused on one technology in one area, making generalizations difficult. In addition, the effect of timing on adoption benefits has rarely been studied *ex ante*. The two studies in this dissertation are aimed at filling these research gaps.

Summary

Two related studies advance our knowledge of the technology adoption process. First, universality is defined, and a test for universality is developed and performed to determine how four factors impact adoption. Factors that systematically relate to the adoption of technology regardless of location or type of technology are called universal. A positive universal factor fosters technology adoption, while a negative universal factor hinders it. Strongly universal factors impact technology adoption in the same way regardless of geography or technology type. Weakly universal factors impact technology adoption, but the magnitude of the impact varies by geography and / or technology type. Factors are not universal if they have no systematic relationship to technology adoption. The test for universality, based on inferences from meta-

regression analyses, is conducted using 170 previous analyses of the adoption of agricultural technologies. Age is found to be weakly negative universal, education and farm size are found to be weakly positive universal, and outreach is not found to be a universal factor.

These results indicate that adoption does not occur in the same way everywhere. Just because a technology is enthusiastically adopted in one area does not mean it will be adopted with such vigor elsewhere. Further, an area that readily adopts one technology may not readily adopt another type of technology. The results also indicate that outreach agents are not a universal factor in the adoption decision. Outreach agents promoting technology adoption may want to reexamine their approaches. Using the results of this study to predict adoption will help technology promoters set realistic goals, target those most likely to adopt, and use their resources more efficiently.

The second study is a case study that examines an emerging information technology, ENSO-based climate forecasts, in various regions of the world. An international wheat trade model is used to examine how the timing of adopting climate forecasts affects the distribution of producer benefits. Various scenarios are examined where wheat producers in the U.S., Australia, and Canada adopt climate forecasts at different rates and in different orders. The pattern of benefits is highly consistent across all scenarios. Earliest adopters gain the most. An adoption ceiling is reached when between 60% and 95% of producers in each country have adopted. The ceiling changes as the rate of adoption changes, with slower adoption leading to a lower ceiling. At the ceiling, the gains to adoption equal the gains to nonadoption, and these gains are higher

than if nobody had adopted. In other words, everybody, even nonadopters, benefit at the adoption ceiling.

Of the three countries, Australia is affected most by ENSO, so it is not surprising that producers in Australia have the most to gain by adopting climate forecasts. These gains vary widely from year to year, however, and in some years, producers may lose if they adopt. As is often the case, there is risk associated with adoption, and the risk varies by location.

Just as the factors associated with adoption are not the same everywhere, the risk is not the same, and neither are the benefits. At the same time, the present study shows there are similarities. Sometimes it is not possible to do a context-specific study. The area may be too large or such a study may be too expensive. In such cases, the similarities can be used. For example, the National Oceanic and Atmospheric Administration (NOAA) is currently involved in promoting the use of ENSO-based seasonal climate forecasts for use in agriculture in the U.S. and abroad. NOAA cannot study the factors or benefits associated with adoption in every region of the globe, but NOAA can use the results of the present study to take advantage of the similarities between areas. NOAA can target younger, more educated constituents with larger farms, while realizing that timing is important. Early adopters gain the most, and quick adoption leads to a higher adoption ceiling. If NOAA is primarily concerned with U.S. benefits and widespread adoption, the Administration can push U.S. producers to adopt early and fast. NOAA must also realize that adoption will only continue until the benefits of adopting equal the benefits of not adopting. When the benefits are equal,

additional producers should not be pushed to adopt. At the same time, NOAA may want to consider the result that conventional outreach programs have not universally led to technology adoption. In addition to targeting those most likely to adopt, innovative outreach techniques need to be investigated.

Limitations and Future Research

Many factors have been associated with technology adoption in the literature, and only four are examined in this study. Additional factors need to be tested for universality to improve technology-promoters' ability to target appropriate audiences. In addition, weak universality needs to be further studied. Technologies and locations can be broken into additional categories to further analyze differences.

Moreover, additional studies examining how the timing of adoption impacts the distribution of benefits are necessary to extend our understanding of the entire adoption process, including its effects. One study is not sufficient to draw general conclusions. More information is needed to help technology-promoters focus their efforts. As the adoption process is better understood, technology-promoters will be able to increase the efficiency of their projects and achieve their goals.

Last, the definition and test for universality are sufficiently general to be extended to other settings. Meta-regression analysis can be used to draw generalized conclusions about factors associated with any number of economic activities. Policy-makers can use these conclusions without wading through hundreds of specific studies. Meta-regression analysis may also reveal the sources of any conflicting inferences, which may stem from studies' methodologies or explanatory variables. Understanding

why studies conflict makes it easier to plan future research projects that will contribute to the literature.

Drawing conclusions from a multitude of studies pulls together the efforts of numerous researchers and allows stronger conclusions to be drawn. In addition, combining the results from diverse studies allows better decisions to be made, as shown by the two seemingly diverse, but actually related studies conducted in this dissertation.

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APPENDIX A

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