Risk

QUANTIFYING LONG RUN AGRICULTURAL RISKS AND EVALUATING FARMER RESPONSES TO RISK

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PREFACE

This publication contains papers presented at a seminar held in conjunction with the 1993 annual meeting of Southern Regional Risk Research Project S-232 held March 24-26 in Jekyll Island, Georgia. This project, entitled "Quantifying Long Run Agricultural Risks and Evaluating Farmer Responses to Risk," is a continuation of two, former regional research projects, W-149 and S-180, in that the research focus is on agricultural risks and farmer responses to them.

This is the eleventh proceedings issue published in the series. Previous issues were published, beginning in 1983, by the agricultural economics departments at the following universities: University of Illinois, Oklahoma State University, Michigan State University, Washington State University, University of Minnesota, North Carolina State University, Texas A&M University, University of Florida, University of Arkansas, and the University of Arizona. This edition was published at the University of Maine.

Cooperating agencies in the S-232 regional research project are the agricultural experiment stations of Alabama, Arizona, Arkansas, California, Florida, Georgia, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maine, Michigan, Minnesota, Mississippi, Missouri, Nebraska, Nevada, New York, North Carolina, North Dakota, Ohio, Oklahoma, Oregon, Pennsylvania, South Carolina, Tennessee, Texas, Utah, Virginia, Washington, Wisconsin, and the Economic Research Service of the U.S. Department of Agriculture, the Farm Foundation, the Federal Crop Insurance Corporation, the National Crop Insurers Services and the Agricultural Library. The project's administrative advisor is Dr. Kenneth Koonce, Louisiana Agricultural Experiment Station, Louisiana State University, Baton Rouge, Louisiana.

Michele Marra served as Chairman of the Technical Committee of the project during 1992-93, while Larry VanTassell served as Secretary-Treasurer. Arne Hallam served as Vice-Chairman and Chairman of the Program Committee, whose members were David Zilberman, Glen Helmers, and Harry Hall. The Farm Foundation provided support for the outside speakers, while the Cooperative State Research Service and the participating experiment stations and agencies provided financial support for the meetings and the publication of the proceedings.

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Managing Groundwater Quality Under Uncertainty

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I. Introduction

This paper addresses strategies for managing groundwater quality under uncertainty. We argue that incorporating notions of contaminant dynamics and the randomness associated with these processes has important consequences for the regulations designed to improve groundwater quality. The paper is divided into three sections. Section 2 develops an economic framework for designing public health regulations, and discusses the proper treatment of uncertainty. Section 3 is a detailed analysis of the interaction between contaminant dynamics and the costs of compliance with groundwater quality regulations. This section highlights the importance of irreversibility in the design of compliance technology. In Section 4, we introduce a blueprint for interdisciplinary analysis of groundwater quality that can be used as a basis for effective and efficient rulemaking.

The discussion in Section 3 is motivated by DBCP (1,2-dibromo,3-chloropropane), an agricultural chemical that commonly found in groundwater. During the 1960s and 1970s, farmers in California used this chemical to control nematodes in grapes, peaches, nectarines and citrus. In the 1970s, it was discovered that DBCP causes sterility in chemical workers and its use was disallowed in 1979. Later, DBCP was detected in groundwater, and the government was faced with developing water quality policies. Once the government established water quality standards, debate ensued regarding costs and methods for treating water in order to meet the standards.

There are two issues associated with the groundwater problem generally, and with DBCP in particular: first, determination of optimal standards for water quality; and second, determination of optimal management policies to meet the standards. In essence, the second problem is a sub-element of the first, because in order to design optimal policies, it is necessary to know their cost. In reality, detailed analysis of costs often does not occur until policies are determined. Further, the role of economists may be more marginal in determining policies than in assessing policies for implementation. Finally, issues related to liability and compensation require detailed analysis of the management problem and can be solved only after the regulation is in place.

One aim of this paper is to provide a basis for discussion and cooperation among the various academic disciplines involved in the study of groundwater contamination. In the environmental area, it is frequently not clear who does what, especially when it comes to intellectual support of regulators, the courts, and private parties. Public health specialists, whose main expertise is in environmental health and risk assessment, often provide information to the regulators responsible for determining water quality and other environmental standards. Engineers, on the other hand, usually provide information to the courts, water districts, and other management agencies about approaches to cleanup and the costs of cleanup activities. Environmental economists need to increase their sphere of influence and convince other parties that they bring something unique and worthwhile to the debate -- namely, the ability to identify trade-off relationships in order to achieve more efficient policies that leave all parties better off.

II. Optimal Groundwater Quality Regulation

Environmental regulators decide on policies (taxes, standards, or any other regulations) to control environmental health problems -- in this case, groundwater management. Lichtenberg and Zilberman (1988) develop a framework simulating some actual procedures which takes into account both the uncertainty faced by policymakers and their response to uncertainty. Environmental regulators measure risk by the probability that an individual will fall victim to a disease or die because of exposure to an environmental hazard. Expected cases of morbidity or mortality per time period provide an alternative measure. Risk measures are random variables subject to uncertainty and randomness. Uncertainty is due to lack of knowledge, while changes in weather patterns or environmental conditions are examples of randomness. Decisionmakers usually factor out uncertainty and randomeness in the decisionmaking process.

Lichtenberg and Zilberman argue that existing regulations (such as the Delaney Clause) can be best described using safety rules. Furthermore, most policymakers in environmental health have been educated in the natural sciences, and they are more at home with classical statistics and confidence intervals than they are with Bayesian statistics and loss functions. Lichtenberg and Zilberman point out that consistent policies should minimize costs with estimated risk levels restricted by an upper bound at a certain degree of reliability.

Formally, suppose that x is a policy tool, c(x) is social cost, and r(x) is estimated risk associated with the policy. Then the objective of the policymaker is to

$$\min c(x) \text{ subject to } \Pr[r(x) < K] \geq \alpha,$$

where K is an upper bound on risk and α is some confidence level.

One of the major implications of this framework is that in order to have efficient policies, all risk estimates should be constructed to provide a certain point of the cumulative distribution of the estimated risk function. For example, if 95 percent is the accepted significance level for policy analysis, then all studies will estimate risk factors that are exceeded with at most five percent probability. Thus, we will obtain consistent estimators and we will be able to obtain consistent values of risk reductions (values of lives saved). Failure to rely on estimates that are obtained with the same degree of statistical reliability may be one of the major reasons why the implicit value of saved lives varies so significantly among different studies.

Using this framework, Lichtenberg, Zilberman and Bogen (1989) develop a model to study DBCP regulation. The health risk regulations for DBCP are the product of three processes: contamination, exposure, and a dose-response function. The regulations considered by the government are uniform standards for drinking water. The standards are implemented by either shutting down wells or using filtering and other technologies.where DBCP contamination is too high.

In computing the costs of the regulations, Lichtenberg et al. assume that every shut-down well is replaced by a deeper well and, therefore, consider the cost of the deeper well. They develop a trade-off relationship between risk and cost for both least-cost and uniform policies.

Figure 1 derives a smooth trade-off curve for the uniform policy where risk is estimated under different levels of reliability. The different risk-cost relationships that were derived under different degrees of statistical reliability show that there are increasing marginal costs associated with increasing reliability used in health risk estimates for the regulatory process.

Figure 2 compares the uniform policy, where water quality standards have to be met by all wells in the Fresno area, with an efficient variable policy, where risk standards are tougher for the city of Fresno because replacing existing wells with deeper wells is more worthwhile in the city where there are more users, while filters are suggested.for the outlying rural areas. Figure 2 shows that both some gains from non-uniform policies and heterogeneity must be recognized in designing environmental regulations. It also shows that the gain from the efficient policy is greater as the degree of reliability of the risk estimates increases. Other studies show much higher gains in costs when one uses variable policies vs. uniform policies.

In Figure 3, the implicit value of excess cancer is derived as a function of the upper level of risk associated with DBCP policy regulation. The analysis demonstrates that the estimated implicit values of life are different under different degrees of reliability for the risk estimates. It is also clear that when upper bounds of risk are estimated with higher degrees of reliability, the implicit value of life becomes much smaller. A similar framework to the one used in the Lichtenberg et al. paper was actually used by the State of California to assess alternative policy, and they decided on a DBCP regulation of 0.2 parts per billion (State of California, 1989).

III. Contaminant Dynamics, Irreversibility and the Costs of Compliance with Drinking Water Standards

In recent years, there has been a trend towards increased awareness of contaminants in the nation's supply of groundwater (Epstein et. al., 1983). Indeed, the Environmental Protection Agency has listed drinking water contamination as one of the primary avenues of human exposure to substances with carcinogenic and other adverse health impacts; groundwater contamination is intimately related to this problem because half of the nation's population relies on groundwater for its supply of potable water (EPA, 1990; Pye and Patrick, 1983; Sun, 1986). The most important causes of groundwater contamination include underground storage tanks, hazardous waste dumps, and agricultural chemicals such as pesticides and fertilizers.

Unfortunately, public demand for maintenance of drinking water safety has outstripped analysis of the cost of such regulations, an assessment of which is fundamental to the design of socially optimal standards. Economic analysis and policy impact assessments have been based on static modelling of contaminant levels and ignore the existence of mobile plumes of contamination. For example, 1,2-dibromo-3-chloropropane (DBCP) contamination is a major environmental concern in California, and cleanup costs for this state alone are estimated by local agencies to be in excess of $1 billion. Studies that consider the costs of compliance with various allowable contaminant levels for DBCP in drinking water, for example Lichtenberg et. al. (1989) and, notably, the State of California's Final Statement of Reasons for its DBCP regulations (1989), do not consider that contaminant levels change dramatically over time. Furthermore, these studies ignore the significant fact that treatment technology can be moved between regions, a characteristic that allows for flexibility and reduces the cost of compliance. This paper presents a new method for calculating compliance costs that explicitly incorporates contaminant dynamics and flexible compliance.

Section III.A describes the class of groundwater contamination problems considered in this paper, and presents the basic framework for computation of capital and operating costs of a water purification system based on well-head filtration. Special attention is paid to contaminant transport, population dynamics, and economic factors such as inflation in the computation of future compliance costs.[1]

In section III.B, we develop two alternative models for computation of the capital costs of compliance via well-head purification. First, the standard method for calculating capital costs assumes permanent, inflexible placement of filtration units. Under the traditional approach, once a filtration unit is acquired and placed on a well head, it remains there; the decision to filter a given well is thus irreversible.[2] We develop the special case of this model in which the contaminant plume is assumed to be completely static, or immobile.

A principal contribution of this paper is the development of a second, alternative approach that incorporates flexibility in the placement of filtration units. We develop a method for building an optimal inventory of filtration devices to be placed on specific wells as needed. When water from a well with a filter in place moves below the standard, the model assumes that the filter will either be moved to another well that exceeds the standard or, more likely, will be moved into storage for use at some unspecified site at a later date. This flexible approach to designing purification systems renders the decision to filter a given well reversible. An important implication of flexibility is that it allows filtration

[1] There are a number of alternative treatment technologies to carbon adsorbtion, including air stripping (aeration), ultraviolet radiation, ozone, and well field management. GAC adsorbtion is a proven method of removing a wide spectrum of organic compounds, including DBCP, and was determined by both the State of California and the USEPA to be the most viable method for removing DBCP and similar substances from ground water.

[2] This term originates from environmental economics, where a number of economists have explored its implications for benefit-cost analysis. (See, for example, Arrow and Fisher, 1974; Fisher, 1984).

devices to mimic the movements of contaminant plumes instead of remaining dedicated to wells that meet standards without filtration.

Section III.C calculates compliance costs for a sample groundwater delivery system under both traditional and flexible well-head treatment systems. We consider the case of Sanger, a municipality in California's San Joaquin Valley, where groundwater used for drinking is contaminated with DBCP.[3] DBCP contamination is perhaps the most severe water quality problem in California, and is a major public health problem in other regions, notably Hawaii, where DBCP has been found in the Pearl Harbor Aquifer. While Sanger is a small city (approximately 18,000 residents), the case study is indicative of the importance of incorporating contaminant dynamics as well as the cost savings resulting from flexibility. Indeed, we show that improperly assuming a static plume and inflexible placement of filters can overestimate compliance costs by over 200 percent. Flexibility is especially desirable when real interest rates are low and when population growth rates are high. In both of these cases, future costs are of paramount importance.

This analysis thus presents a method for calculating the social costs of water quality regulations taking into account the dynamic processes of contaminant transport that govern water quality over time. The model of compliance strategy presented here incorporates these dynamic processes, as well as those determining population levels and prices. This model also considers the impact of transferability of cleanup systems. Existing models of the social cost of environmental and public health regulations ignore these dynamic considerations, and in particular do not consider the importance of contaminant movement and flexibility in the design of compliance measures. Section III.D discusses the importance of these considerations for the design of appropriate water quality regulations. To the extent that standard analyses of compliance costs mis-estimate social costs by ignoring contaminant movement, these procedures lead to suboptimal public health standards.

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[3] Other common pesticides known to contaminate groundwater include Aldicarb, Atrazine, Bentazon, Bromacil, Chlorothalonil, 2,4-D, Diuron, EDB, Endothall, Prometon, and Simazine.

III.A. The Compliance Cost Model

Consider a city providing groundwater that is extracted by a predetermined number of wells to its residents and businesses. We consider a general dynamic situation in which the water delivery system serves a variable number of people. Suppose that the city's population is growing at a rate ρ. The current water delivery system has a capacity of M gallons per minute, and the capacity of each well is G gallons per minute. The number of wells needed to service a growing population at each time, or n_t, is then described by

$$n_t = I\left(\frac{Me^{\rho(t-t0)}}{G}\right),$$

where $I(\cdot)$ is a function assigning to any real number the nearest integer equal to or exceeding that number. The number of wells comprising the system thus grows in discrete jumps to accommodate new residents.[4]

Suppose that the groundwater beneath the city is contaminated by some substance with adverse health impacts. More specifically, consider a situation in which there is a mobile plume of contaminant in the groundwater. The existence of a plume of contamination implies that contamination may be a localized phenomenon, that is, the contaminant may not be observed in all wells at all times. The mobility of the plume implies that different wells may be contaminated at different points in time. Given the large degree of scientific uncertainty regarding plume movement, it is natural to model contamination for a given well as a stochastic process. Let the random variable θ_{it} represent the level of contamination in well i at time t expressed in units such as parts per billion (ppb), and let σ_{it} denote the standard error of the contaminant level for well i at time t.

It is frequently the case that there is some regulatory agency overseeing the provision of potable groundwater and enforcing quality standards. For example, the

[4] This formulation assumes a constant system gpm per capita. It is possible to endogenize system capacity by making per capita demand dependent on price.

Federal Safe Drinking Water Act regulates the presence of harmful substances in drinking water, and empowers the U.S. Environmental Protection Agency to enforce compliance. Regulations regarding drinking water quality typically take the form of maximum allowable contaminant levels (MCL), expressed in terms such as ppb, that must be met for all wells at all times.

Combining expected contaminant levels described earlier with these standards, define the probability that water from well i exceeds the MCL in time t as

$$P_{it} = \Pr(\theta_{it} > MCL).$$

For example, if the contaminant level is distributed $N(\mu_{it}, \sigma_{it}^2)$, then P_{it} is determined as

$$P_{it} = F\left(\frac{MCL - \mu_{it}}{\sigma_{it}}\right),$$

where $F(\cdot)$ is the standard normal distribution function. Note that a special case of this model is one in which the contaminant plume is assumed to be completely static. In this case, $\theta_{it} = \theta_i \ \forall \ t$, and

$$P_{it} = \begin{cases} 1 & \text{if } q_i \geq MCL \\ 0 & \text{else} \end{cases}$$

We will explore this commonly assumed, but highly unusual, scenario in detail below.

One reason that the contamination of groundwater is a particularly serious problem is that groundwater is virtually inaccessible, making direct cleanup nearly always economically impractical. Thus, the most common strategy for meeting drinking water standards is to purify groundwater after it is extracted, typically by filtration units installed at the well head. We consider such a compliance strategy below.

There are two types of compliance costs involved in the construction and operation of a filtration system: capital and annual costs. Capital costs are incurred once for each filter, and are expended upon installation of the filtration unit. These costs include the cost of the filtration unit itself, pipe, land, labor, permitting, system design, and monitoring. Annual costs are incurred only for the time that the filtration unit is in service. These costs include the cost of the filtration medium, waste disposal, labor and physical depreciation. Total compliance costs in year t are represented as

$$TC_t = \sum_{i \in N_t} [K_{it} + V_{it}]$$

where N_t is the set of wells comprising the system in year t, K_{it} is the capital expenditure on well i in year t and V_{it} are the annual costs for well i in year t. For ease of exposition, we assume that capital expenditures are either K or 0 for all wells, and annual expenditures are either V or 0 depending on whether the unit is in service.

Capital costs are expended upon installation of a filtration unit. We assume throughout this paper that all wells with contaminant levels exceeding the relevant MCL receive a filtration unit. This feature of the model assures that drinking water will meet health standards at all times. Expected capital costs are a principal focus of this paper and will be discussed in detail below.

Variable costs are expended only when a filtration unit is installed on a well that exceeds the MCL. Expected variable costs at time t are simply the costs of actual operation of a filtration unit multiplied by the probability that the unit is in service.

We now turn to a discussion of two methods for calculating expected capital and total compliance costs under the irreversible and flexible approaches.

III.B. Compliance Costs

III.B.1. Inflexible System

The standard method for calculating the capital costs of compliance with drinking water standards is to predict, for a given tolerance level, the number of wells exceeding that level and install a filtration device on each of those wells. These units are then dedicated to their respective sites. Estimating capital costs under the traditional method requires that we calculate the probability of making the capital expenditures necessary to fit a well with a filtration unit at each time period. This calculation is complicated by the fact that such an expenditure is only made once.

The probability of making the capital expenditure on well i at time t under inflexibility is calculated as

$$R_{it} = P_{it}\prod_{\tau<t} (1-P_{it}).$$

That is, the probability of installing a filtration device at time t is the probability that the well exceeds the MCL at time t and that it has not exceeded the MCL at any time prior to t. Expected capital expenditures at time t under the inflexible methodology are simply

$$EK_t^I = \sum_{i\in N_t} R_{it}K,$$

where K is the capital expenditure required to install a filtration unit.

Expected annual expenditures are calculated as operating costs, V, multiplied by the probability that a filtration device is required on well i at time t, or

$$EV_t = \sum_{i\in N_t} P_{it}V$$

This expression assumes that while filtration units are immobile under the standard methodology, they are not operated unless the water at the site exceeds the allowable contaminant level.

It is instructive to write out compliance costs under the assumption of a static plume. In this case, as discussed previously, $\theta_{it} = \theta_i \ \forall \ t$, and contaminant levels are nonstochastic. Denoting the first year a well can be filtered as t_0, it follows that

$$R_{it} = \begin{cases} 1 & \text{for } t = t_0 \text{ if } \theta_i \geq MCL \\ 0 & \text{else} \end{cases}$$

All other expressions are calculated as before. Note that since the location of future wells is typically unknown, it is reasonable to assume with a static plume that a future well will exceed the MCL with a probability equal to the likelihood that a randomly selected member of the existing set of wells will exceed the MCL. This presumption is equivalent to assuming a random placement of additional wells.

Total compliance costs are current system costs plus the present value of future costs. Future costs are discounted at the real interest rate, or the nominal interest rate minus the rate of cost inflation, to make them comparable to present dollar costs. The present value of expected compliance cost is calculated as

$$PV = \sum_{t=0}^{\infty} \frac{EK_t + EV_t}{(1+r)^t},$$

where r is the real rate of interest calculated as the nominal interest rate minus the rate of cost inflation.

III.B.2. Flexible System

Expected capital costs with a mobile compliance system are determined by calculating the expected filter inventory size that ensures each well above the MCL receives a filtration unit. This number is the difference between expected filter demand and the inventory existing at time t as a result of past purchases. Expected system demand for filters is calculated as

$$ED_t = \sum_{i \in N_t} P_{it}$$

The expected supply of filters, or inventory, at time t is equal to the expected number of units in service during the period of peak demand, or

$$ES_t = \max_{t<t} \{ \sum_{i \in N_t} P_{it} \}$$

Thus, expected capital expenditures with a flexible system are given as

$$EK_t^F = \max\{ \sum_{i \in N_t} P_{it} - ES_t, 0\}$$

As before, expected annual expenditures are $EV_t = \sum_{i \in N_t} P_{it} V$.

It is straightforward to demonstrate analytically that $EK_t^I \geq EK_t^F$. Since the traditional system is a constrained version of the flexible system, minimum compliance costs under the former must be no less than under the latter. Costs under either system increase with the real interest rate r and the population growth rate ρ. The difference in compliance costs will increase as r increases and also as r decreases.

Before moving to our empirical example, we note that a stronger version of flexibility is an inter-system market for filtration devices. In this case, filtration units are traded among water delivery systems. Such an institution removes all capital costs for filtration units since units could be purchased when needed and resold in the event of an excess supply, or simply rented from third parties. The appropriate treatment of the cost of filtration units in this case is as an annual expenditure since temporary acquisition of filters is tantamount to rental. We will discuss this modification of our basic model in the concluding section.

III.C. Empirical Example

In an effort to gauge the empirical significance of contaminant transport and irreversibility, we consider treatment costs for a particular water system under various assumptions regarding plume dynamics and compliance technology. The example considered here is the town of Sanger, California, located in Fresno County. This municipality, like many others in the Central Valley, has been mandated to reduce the level of residues from DBCP, used extensively on surrounding vineyards and orchards for nematode control, to a level of 0.2 ppb. Figure 4 shows the area of potential DBCP contamination in California and places Sanger in this affected area.

Sanger's water delivery system serves slightly more than 4,000 businesses and households and draws water from 11 wells placed at various locations throughout its service area. The system currently has a capacity of more than 10,000 gpm. Figure 5 shows a stylized description of the city, and gives the placement of the existing wells.

DBCP levels at a number of wells are far in excess of the MCL. Concentrations have been recorded as high as 10 ppb, and levels in excess of 5 ppb are common. There is, however, substantial fluctuation in the contaminant level over time and between wells, indicating plume movement. Hydrogeologists familiar with the Sanger area indicated the direction of groundwater flow, and hence plume movement, which is shown in Figure 5. The time pattern of actual contaminant levels in Sanger give broad support for the idea of a dynamic plume of contamination moving in this direction. Figure 6 plots the date of peak DBCP levels in each of Sanger's wells against their distance from an arbitrarily selected line perpendicular to the hypothesized direction of flow. There is a strong correlation between downgradient distance and peak date, suggesting that fresh water recharge is moving the plume in the direction indicated in Figure 5.[5]

Calculation of current and future compliance costs by either the standard or flexible methods described above requires an assessment of future contaminant levels. We form these expectations by building a time series model of actual DBCP levels at each of the wells comprising the system and using this model to estimate the mean and variance of future contaminant levels. The empirical model assumes that DBCP levels are governed by a gamma distribution; that is

$$\ln\theta_{it} = \ln\alpha_i + \beta(t-t_i^*) + \ln\gamma(t-t_i^*),$$

where t_i^* is the date of the peak observation for well i. This transformation of time aligns the peaks for all wells and allows for pooled estimation of the parameters α_i, β and γ. The parameters β and γ are common to all wells and describe the process by which contaminant levels change over time, while the coefficients α_i account for well-specific deviations from the common trend. The gamma formulation is commonly used to model processes involving failure time and decay. (Cox and Oakes, 1984)

Measurement of contaminant levels in Sanger occurs at irregular intervals and on different days for different wells, but were taken on average approximately once per

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5 The speed of plume movement implied by Figure 3 is approximately 1.5 feet/day, which is highly plausible.

month. These data reveal significant amounts of DBCP contamination, but also indicate that contaminant levels are declining in many locations. Casual observation of the data supports the use of a gamma distribution for modelling the contaminant level time series since contaminant levels are unimodal and are an asymmetric function of time.

The statistical model is estimated via ordinary least squares based on data for the period 1984 to 1991. The estimated component of the forecast that is common to all wells is

$$\ln\theta_t = \underset{(0.00004)}{0.00021t} + \underset{(0.10582)}{0.94824\ln t},$$

with standard errors in parentheses. Coefficients for these parameters are highly significant.

Contaminant levels at wells to be constructed in future periods are estimated by assuming that these wells have the characteristics of a randomly selected member of the set of original wells. Future contaminant levels employed in the cost analysis, denoted q_{it}, are the mean forecast values from this time series regression, and standard errors of the future levels are calculated as

$$\sigma_{pred} = \sigma[x_0(X'X)^{-1}x_0 + 1]^{1/2},$$

where σ is the standard error of the regression, x_0 is the vector of independent variables for the observation to be predicted, and X is the entire pooled data matrix. (Judge et. al., 1985) The probabilities P_{it} and R_{it} are then calculated by forming Z-values for each well and finding the corresponding value of the standard Normal distribution function at this point.

It is instructive to examine the model results for a randomly selected well. Figure 7 shows the estimated probability that the DBCP level exceeds the MCL in new wells. The decline in contaminant levels predicted by the statistical model is not surprising given the fact that DBCP usage was halted by regulatory action in 1979 and that the nearby King's River recharges the aquifer underlying Sanger with uncontaminated fresh water.

We now examine compliance costs costs under a variety of models. We begin by calculating compliance costs assuming a static contaminant plume. This assumption is the basis for most calculations of compliance cost, including the estimates used by the State of California in justifying the allowable DBCP level of 0.2 ppb. Under this assumption, it is necessary to install filters at all wells currently exceeding the MCL and install filtration devices on new wells exceeding the MCL. As discussed in Section 3, the probability that a new well will exceed the MCL in this approach is simply the fraction of current wells needing treatment. This assumption is appropriate since the physical location of additional wells is uncertain, and we know that a fraction of the area underlying Sanger is currently contaminated. Note also that flexibility is incompatible with the notion of a persistent, spatially static plume. Permanent placement of filters is the only viable compliance strategy under this assumption.

Table 1 gives compliance costs assuming a static plume for a various combinations of population growth rates and real interest rates. The scenario of a 2.5 percent population growth rate and a two percent real interest rate is the most likely combination of these variables, and is based on the State of California's assumptions about population growth in Fresno County and about general price inflation relative to compliance costs. Total compliance costs for this case are $12.778 million, measured in 1992 dollars.

We now consider the empirical importance of modelling contaminant dynamics and flexible compliance. Figure 8 gives expected nominal capital costs under both inflexible and flexible approaches assuming a population growth rate of 2.5 percent, a real interest rate of two percent, and contaminant dynamics as forecasted by the statistical model. In this case, capital costs for either the inflexible or flexible systems are determined through the interplay of two forces. DBCP levels are expected to decline as the plume moves away from Sanger, and thus the capital and annual expenditures for a given well should decline over time. However, the need for the water system to service a continuously growing population implies that there will be more potential sites needing filtration devices.

Consider capital costs for the inflexible compliance strategy. Capital costs in the first year are incurred to service those wells in the original set of 11 that exceed the MCL. Capital costs then decline as a function of both declining probability of violating the MCL and of past probabilities of installing filtration devices. In 1997, however, expected capital expenditures then spike because a new well will be installed in that year; they then fall for the same reasons as before.

Expected capital costs for the flexible compliance strategy follow a different path over time. Capital costs are the same in the first year as under the traditional strategy since they are derived solely as a function of the number of the existing 11 wells that exceed the MCL. Between 1992 and 1997, expected capital costs are zero under flexible compliance; the expected demand for filtration devices is declining throughout this period since expected contaminant levels are declining, and expected supply remains constant. When the first new well is installed in 1997, capital costs are less under flexible compliance than under traditional compliance since there is some chance that the existing inventory of filtration devices is sufficient to service all wells, including the new well. This probability grows over time as a reflection of the general decline in contaminant levels so that expected capital costs fall to zero in the year 2007 and remain at zero thereafter.

Table 1 presents the present value of total expected compliance costs for the three models of compliance costs under an array of key model parameters. These results demonstrate that incorporating contaminant dynamics and flexibility have a dramatic effect on compliance cost, especially when future considerations are of paramount importance. For the baseline scenario of a 2.5 percent population growth rate and a two percent real interest rate, compliance costs are overestimated by 61 percent by assuming a static plume, and by 28 percent when contaminant dynamics but not flexibility are assumed. In the scenario of five percent population growth per annum and a two percent real interest rate, ignoring contaminant dynamics and flexibility overestimates compliance expenditures by 265 percent

While this example represents one municipality, the magnitude of the percent changes in cost estimates between models are highly revealing. It is important to remember that the lesson to be drawn from this example is not that compliance costs are systematically underestimated by assuming a static plume; indeed, if a plume of contaminated groundwater is moving towards a water delivery system, then assuming a static plume may underestimate compliance costs. Rather, this example indicates the importance of incorporating contaminant dynamics and flexibility into the calculation of compliance costs.

III.D. Discussion

The design of efficient groundwater purification systems is a public health problem of the highest importance, and measuring the cost of compliance with drinking water standards is a prerequisite to designing appropriate regulations. This section develops a method for calculating compliance costs in a dynamic framework, and focuses attention on the benefits of incorporating plume movement and flexibility in the placement of purification devices in models that calculate compliance costs.

This paper demonstrates both analytically and in the context of an empirical example that flexible, or reversible, compliance strategies always have lower costs than systems with immobile filtration devices. When groundwater contamination is localized because contaminants travel in plumes, flexible compliance allows the purification devices to migrate with the contaminant, and thus be used only where and when they are needed.

The possibility of flexible compliance has important implications for the design of efficient drinking water regulations. The approach taken in this paper is not to find the first-best drinking water standard. Instead, our model is in the spirit of Baumol and Oates (1975), who suggest that economists identify policies that minimize cost given compliance with pre-specified environmental objectives. This approach is consistent with the recent work of Lichtenberg et. al. (1989). They advocate the imposition of public health standards to minimize the social cost of meeting a safety rule specifying that risk remains below a maximum allowable level within a given margin of safety.[6] Stated alternatively, their approach seeks to minimize social cost given the constraint that risk exceeds some maximum level with no more than some pre-specified frequency. The consequence of assuming a static plume and irreversibility in the placement of filtration devices is, under their method, an inappropriate drinking water standard.

It is difficult to make *a priori* judgments about the direction of bias. Both methods require an assessment of the marginal cost of the proposed standard, or the incremental change in total cost incurred by a marginal decrease in the allowable contaminant level. While we do know that the integral of marginal cost, or total cost, must be lower under flexible compliance for any given MCL, it does not follow that the marginal compliance cost for a flexible system is lower than that for an inflexible system. We suspect, however, that empirical analysis will confirm that marginal compliance cost is lower for a flexible system, at least over the relevant range of standards. In this case, assuming irreversibility leads to inefficiently lax drinking water standards.

Finally, note that the analysis presented here assumes a restricted form of flexibility in that filtration units can be moved only within a given water system. The benefits of the flexible approach described here will increase with the advent of an inter-system market for filtration devices. Such a trading mechanism enables purification equipment to follow contaminant plumes beyond water district boundaries. A closely related scenario is a private rental market for filters. The existence of such a market poses an interesting problem for water utilities: whether to lease or buy filtration devices upon discovery of a groundwater contamination problem.

IV. Extending the Rulemaking Model

The model in the previous section that computes the cost of meeting policy regulations has numerous implications for the policy assessment process that are presented

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[6] An alternative approach is to derive uncertainty-compensated trade-offs between risk and social cost. (Lichtenberg and Zilberman, 1988)

in this section. Reassessing the analysis of the policy model of Lichtenberg et al. (1989) suggests that this model is static and does not take into account dynamic phenonmena such as population growth, plume movement, etc. Moreover, the static analysis also has very important implications for the health risk estimates, since, as the plume moves, risk to some water users declines, while other users face greater risks. At this stage where there is a scarcity of modeling to assess environmental health and production trade offs, even static analysis may represent great progress, but future efforts should emphasize dynamic modeling both of costs and health risk processes. In this section, we suggest how to extend the policy framework to incorporate important time-dependent processes at work in the physical and economic environment that affect both the costs and benefits of public health standards.

Suppose the population is spread over a region and there is underground flow of water which is used for drinking. There is a plume of contaminants that moves underground and contaminates the water. Let r denote location. Let t denote time index. Let $N_\alpha(t)$ denote the number of estimated excess cancers in year t that is not exceeded with probability α. Let $\theta(r,t)$ be the contaminant level at r in t, let $n(r,t)$ be population at r in t, let $e(x,t)$ be per-capita exposure in t as a function of some policy x (for example, the price of drinking water), and let c be a dose-response parameter. Assuming that the risk-generation function is the product of contamination, exposure and dose-response processes, for every realization of each of the random processes define

$$N(t) = \int_R \theta(r,t)\, n(r,t)\, e(x,t)\, c\, dr.$$

$N(t)$ is a random variable. Then,

$$\Pr\,[N(t) \le N_\alpha(t))] \le 1-\alpha$$

Now let V_α be the value of excess cancer with a significance level α, let μ be the maximum allowable contaminant level, and let $CL(\mu,t)$ represent compliance cost under regulation μ in year t. Then the optimal time-invariant uniform water quality regulation is found as a solution to

$$\min_{\mu} \int_{T} e^{-\rho t} [CL(\mu,t) + V_{\alpha}E(N(t))]\, dt$$

This formulation implies that there is an asymmetry between the reliability of estimators of health risk and compliance costs. Thst is, the optimization problem assumes a higher degree of risk aversion with respect to health than cleanup expenditures.

There are several important sources of uncertainty that enter in to the rulemaking algorithm just described. They concern uncertainty about the health risk of groundwater contaminants, the physical environment, the economic environment, and compliance technology.

Toxins found in groundwater have uncertain affects on humans. As the science of toxicology progresses, it is likely that there will be a reevaluation of the health risk of these contaminants. Some substances might even be added to the list of harmful substances known to exist in groundwater. Radon, for example, is an emerging threat to public health. Further, detection technology is improving.

A second important source of uncertainty is hydrodynamics. While it is possible to model plume movements, there is some error associated with these forecasts.

There are likely to be significant changes in the economic environment that affect both the cost and benefit of groundwater quality regulation. There is uncertainty surrounding population growth rates, discount rates, and policies determining exposure such as water prices. There might also be regional markets for compliance technology, as discussed in the last section, that significantly reduce the short-term costs of cleanup.

Finally, there are likely to be significant changes in compliance technology that affect the costs of regulation. There are a number of scientists currently working on the problem of DBCP cleanup, for example. To the extent that these technologies reduce the cost of compliance, there is a benefit to adopting short-term cleanup strategies that are reversible, or that avoid commitment. It is quite likely that California will have a surface water market in the near future. In this case, municipalities could simply purchase relatively high-quality water on this market, thereby avoiding the necessity of cleaning groundwater. It is thus optimal to encourage reversible investments in compliance technology in the short-run.

An important related set of issues concerns the implications of jointness in compliance technology. Many methods of removing a particular contaminant, including GAC filtration, remove a wide array of other harmful substances. There is thus an economy of scope in the compliance technology. As a result, it is important that, at a minimum, regulations on allowable contaminant levels be formulated simultaneously and not sequentially. Further, this observation demonstrates the need for a cost allocation algorithm similar to those developed in the regulated industries literature (e.g. anonymous equity, fully distributed cost, Shapley value).

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FIGURE 1

COST-RISK TRADEOFFS - LEAST COST vs. UNIFORM STANDARDS

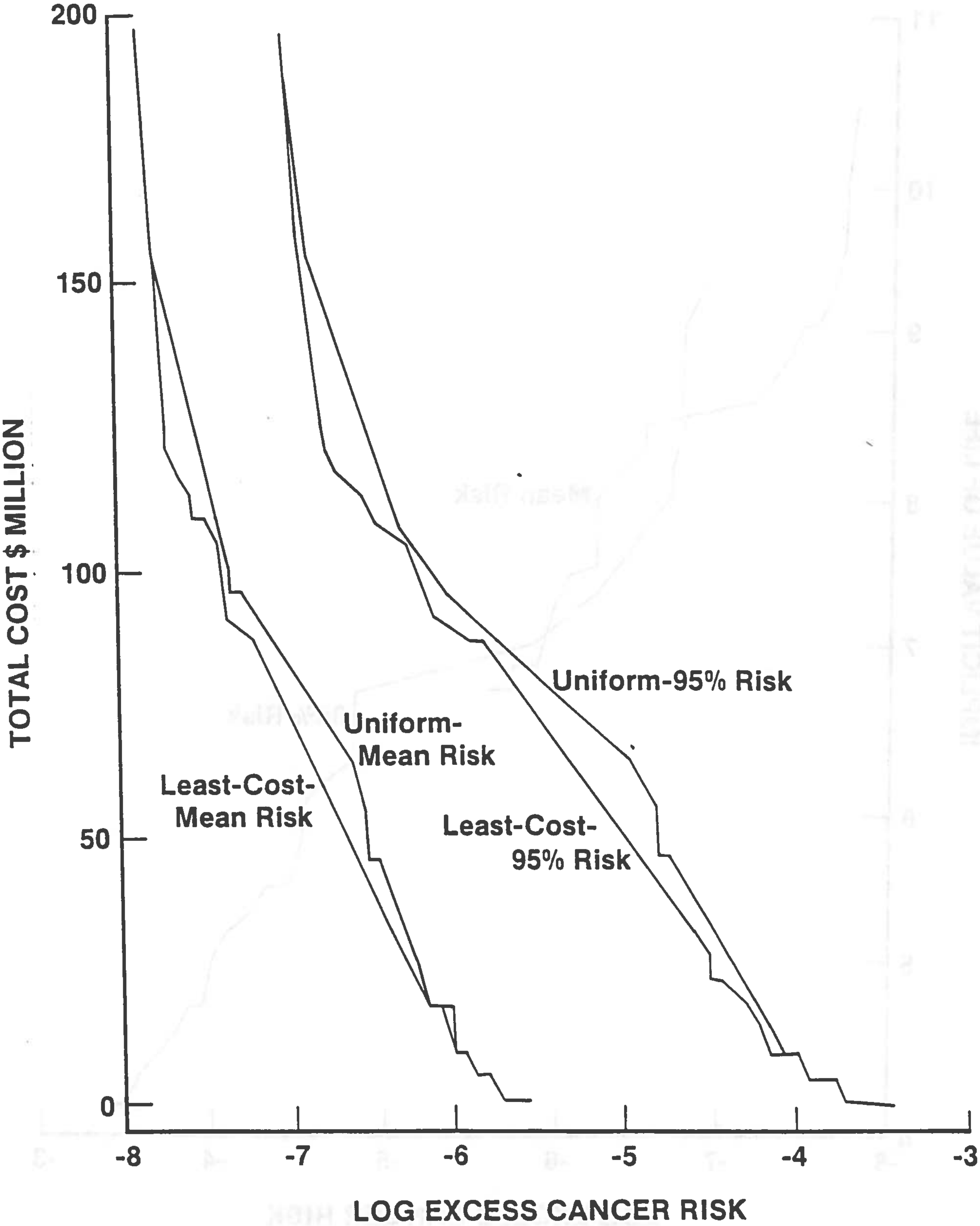

FIGURE 2
IMPLICIT VALUE OF LIFE - 95% vs. MEAN RISK STANDARDS

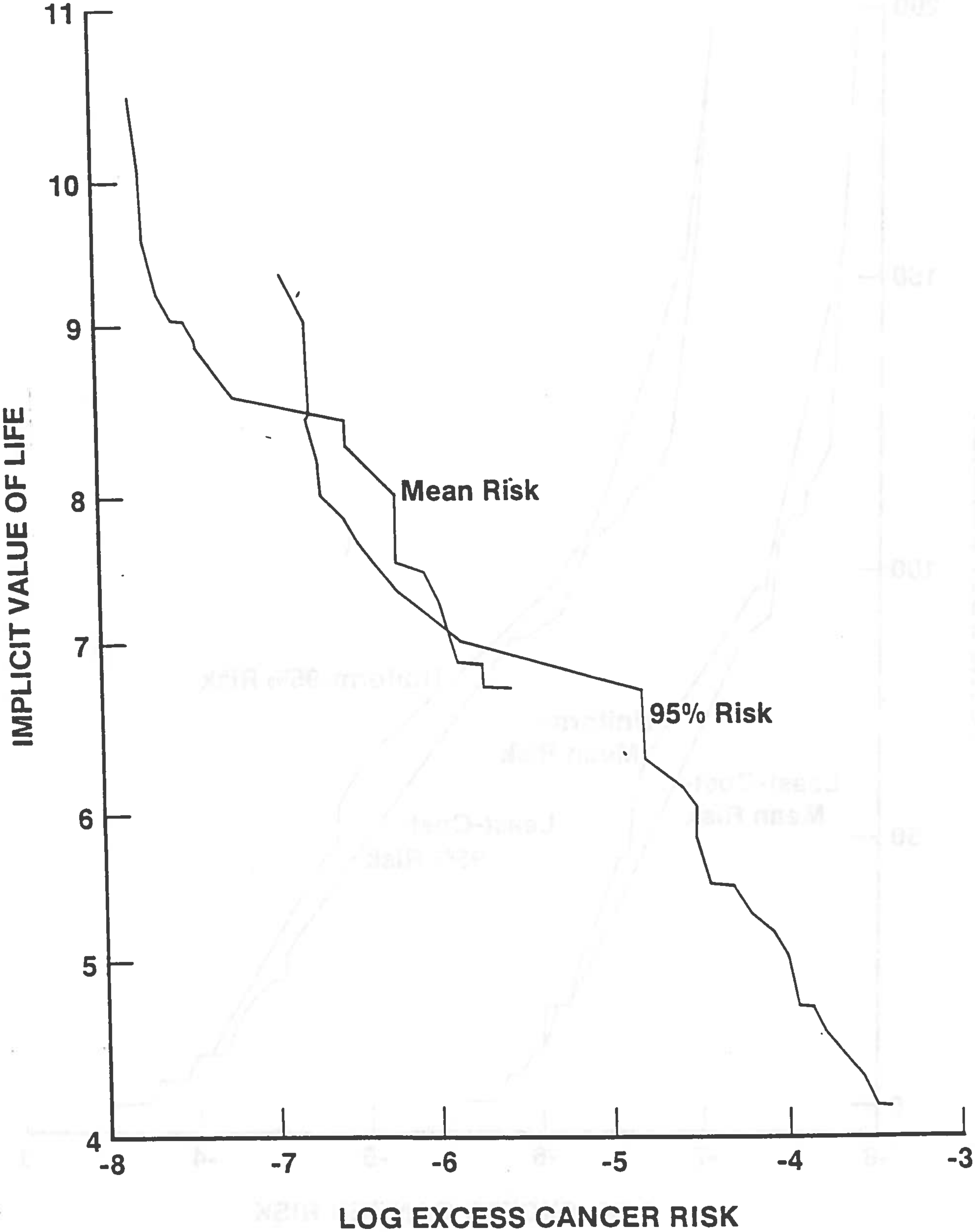

Figure 3

Smoothed Tradeoff Curves for DBCP in Well Water, Fresno County, California

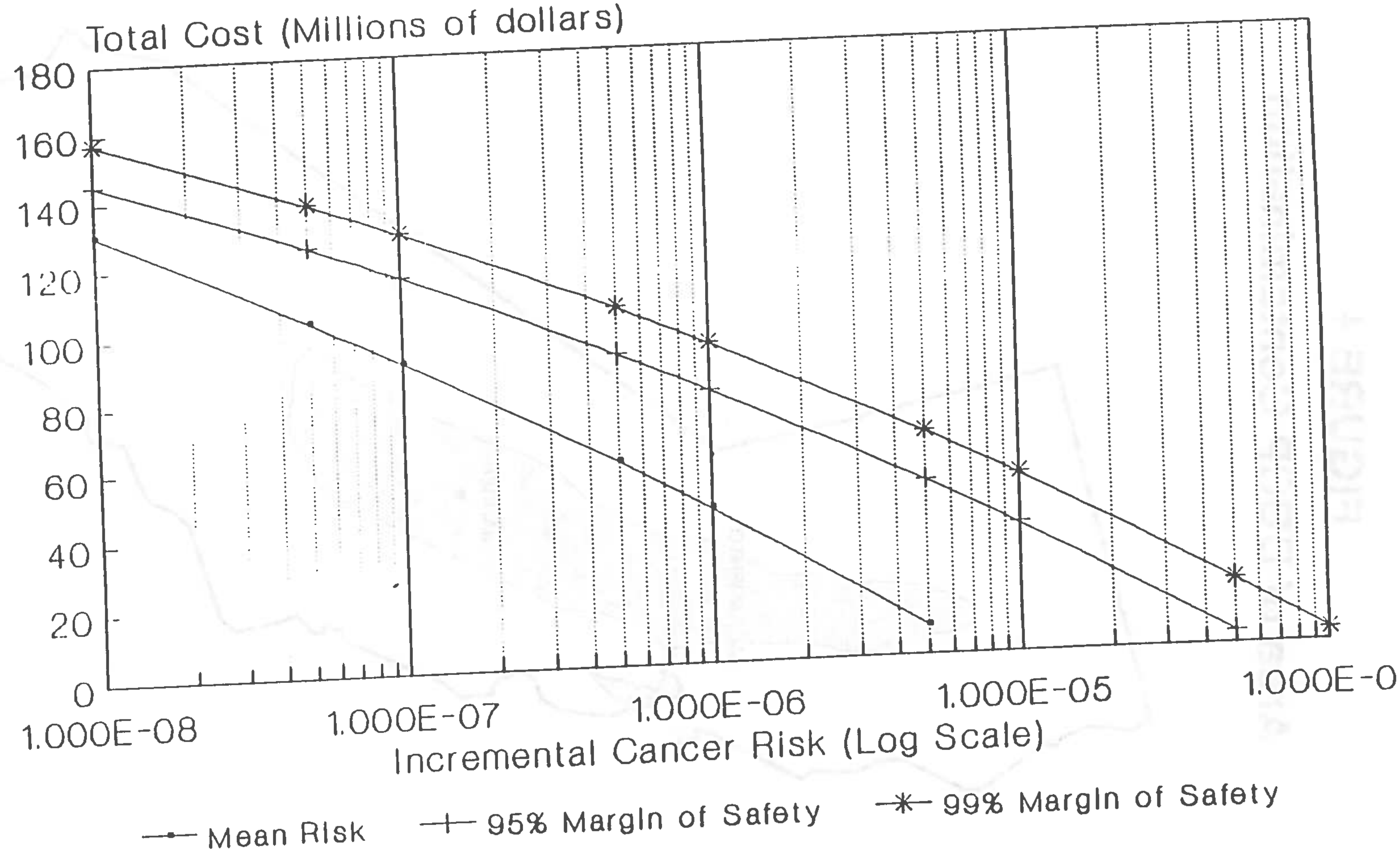

FIGURE 4
Area of DBCP Contamination

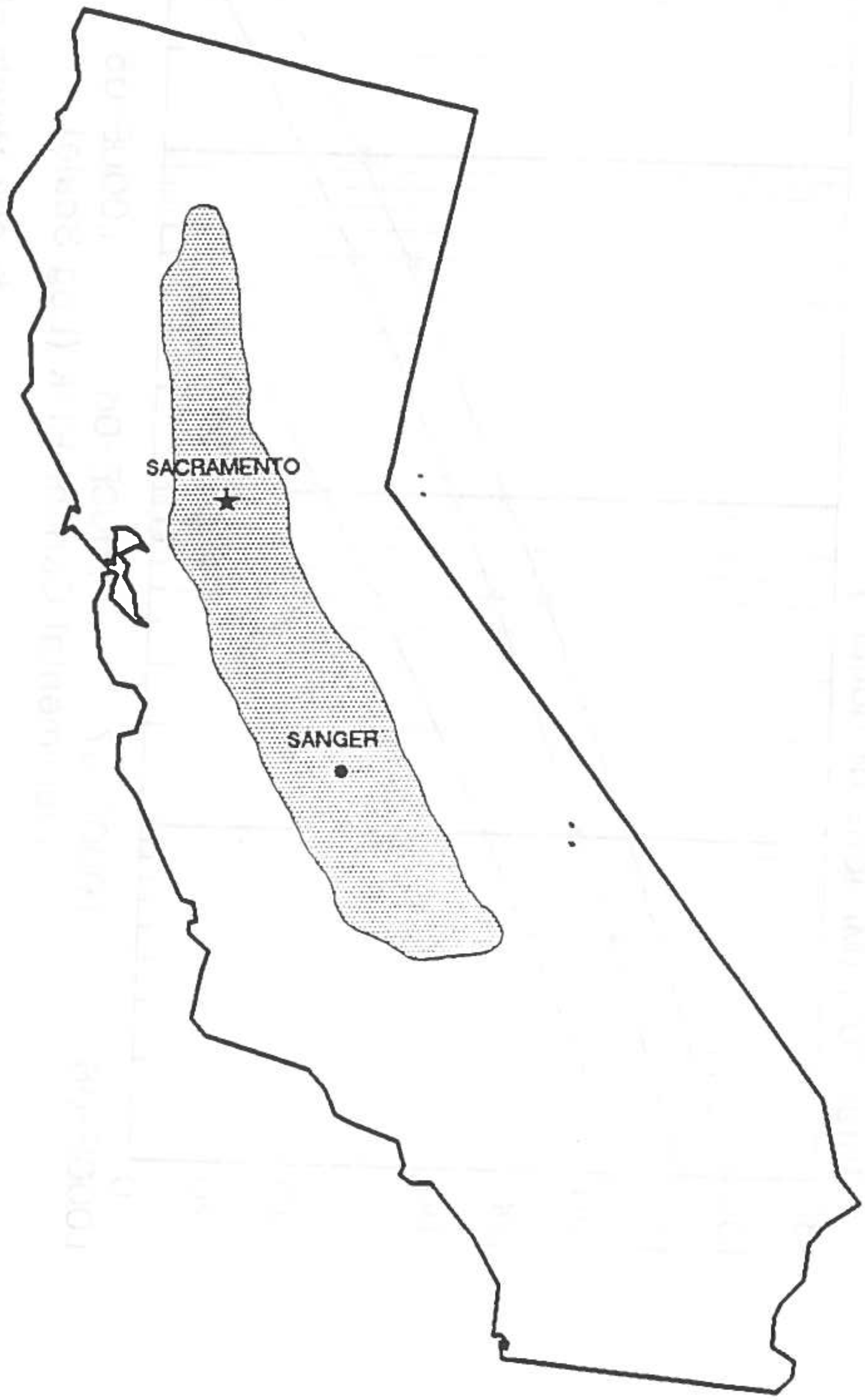

FIGURE 5

Location of Drinking Water Wells in Sanger

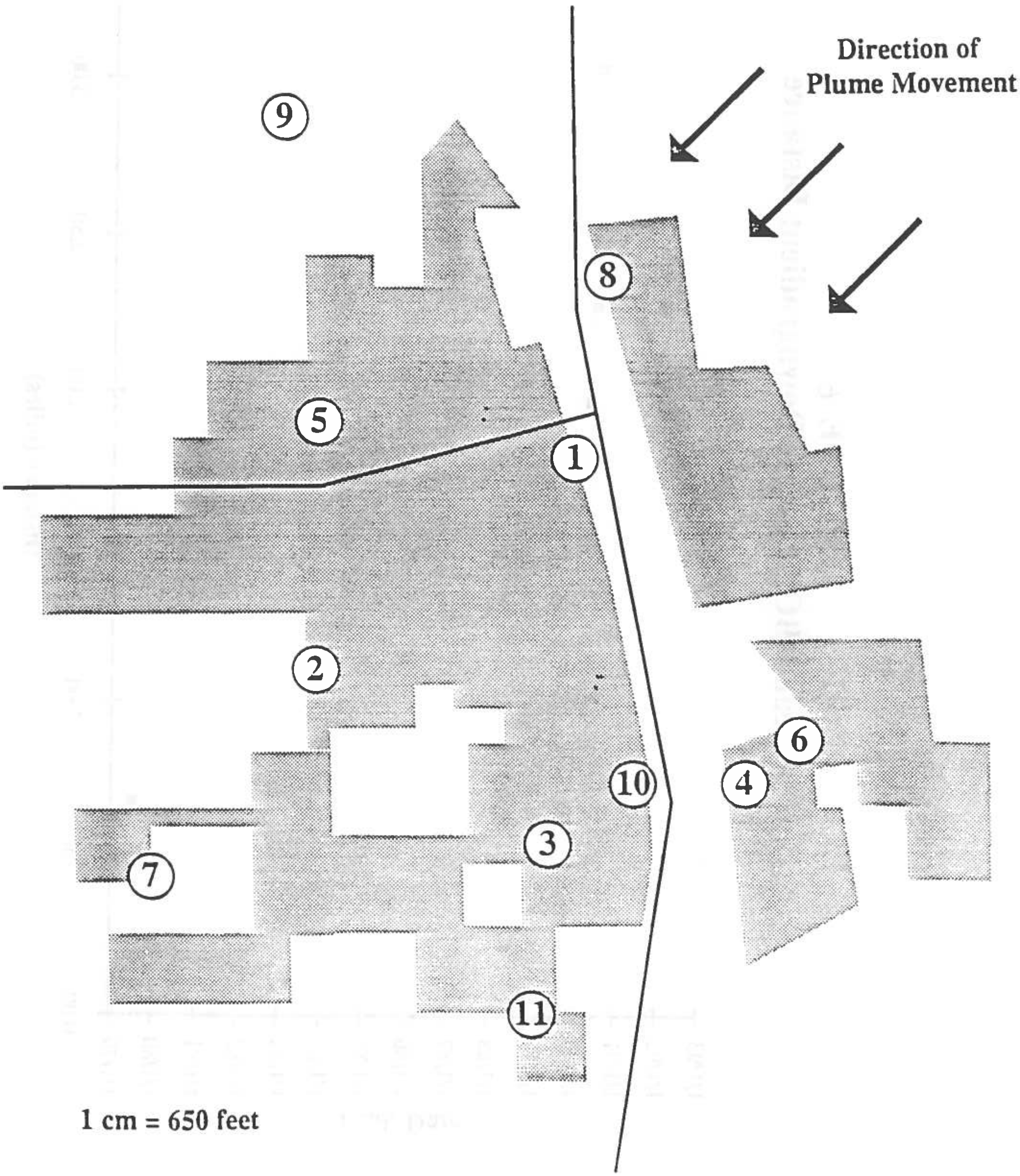

FIGURE 6
Date of Peak DBCP Level v. Downgradient Distance

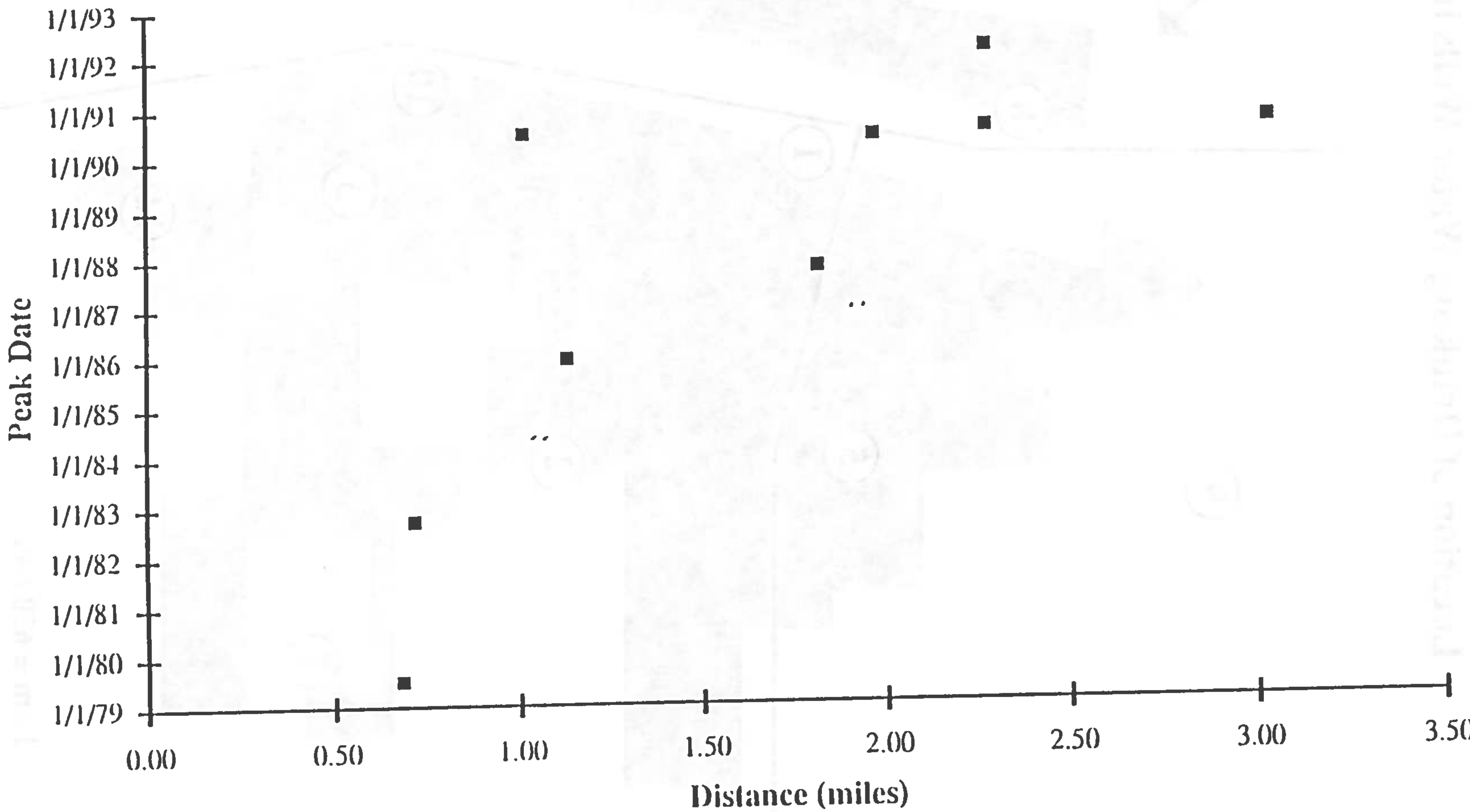

FIGURE 7

Probability that a Randomly Selected Well is Over the MCL

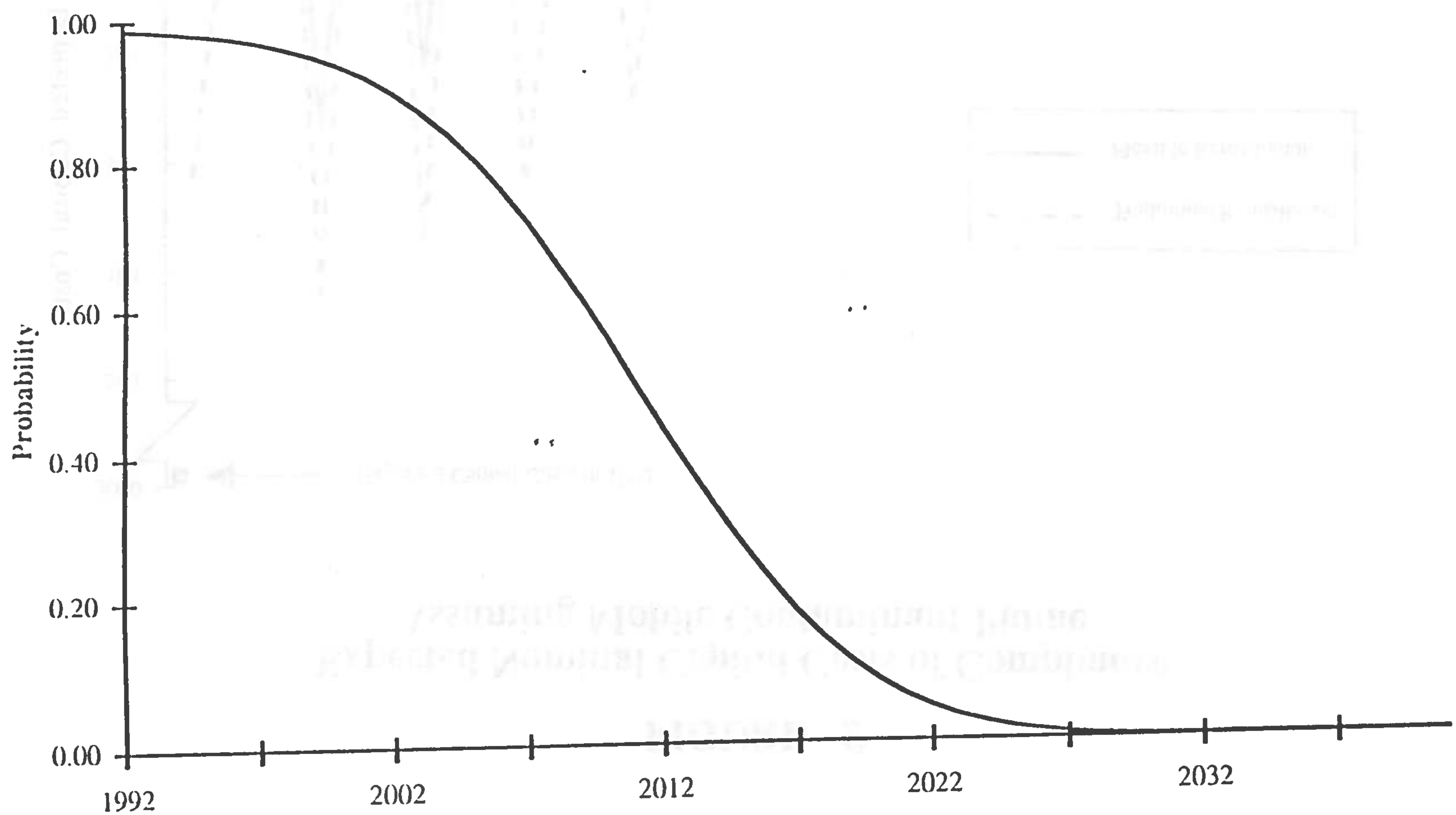

FIGURE 8

Expected Nominal Capital Costs of Compliance Assuming Mobile Contaminant Plume

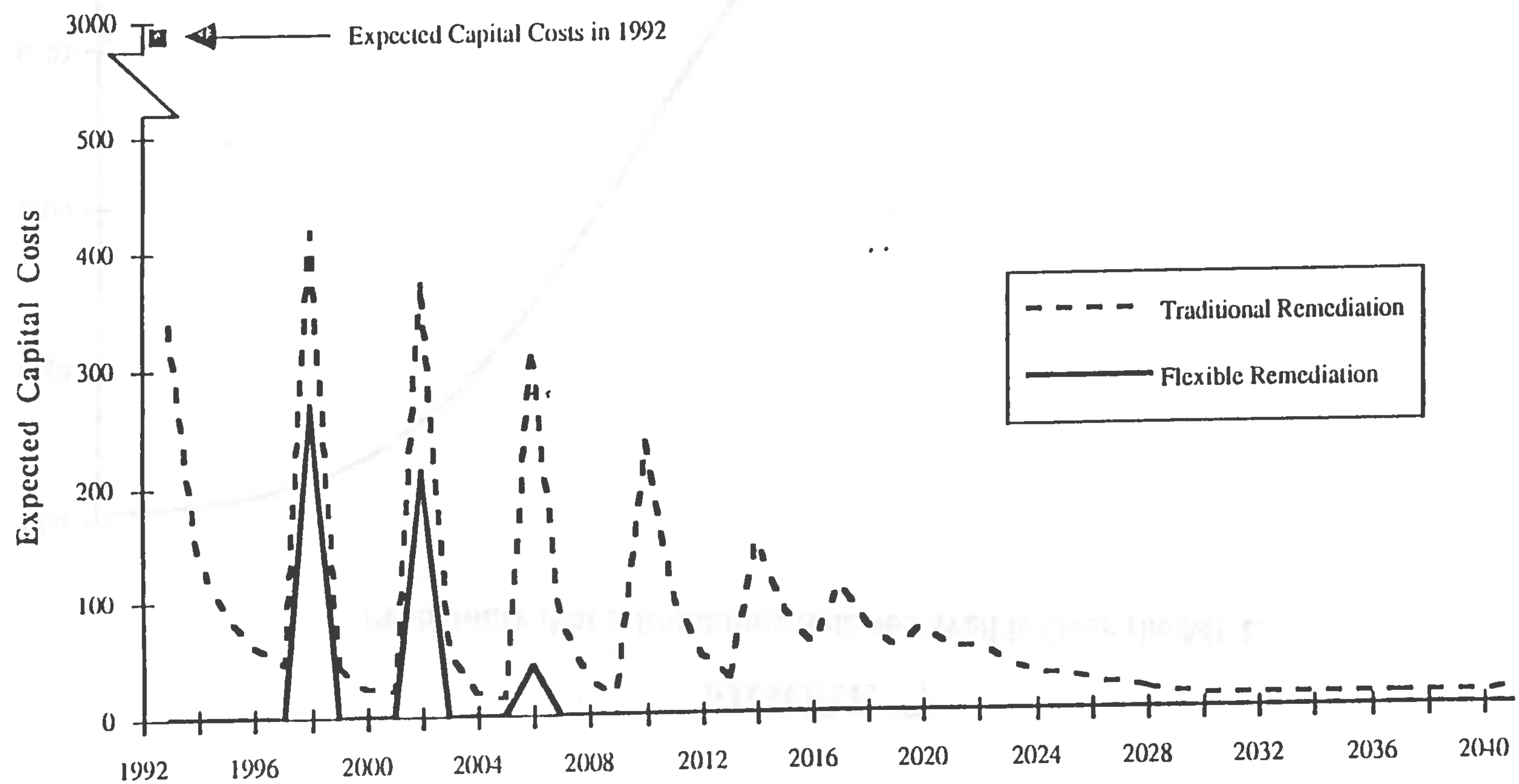

TABLE 1

Present Value of Total Compliance Costs

Discount Rate	Population Growth Rate	Static Plume	Dynamic Plume, Inflexible System	Dynamic Plume, Flexible System
(percent)		(thousands of dollars)		
0.0	0.0	10,133	9,707	8,132
	2.5	19,905	12,904	9,889
	5.0	45,980	19,004	12,614
2.0	0.0	7,506	7,955	6,580
	2.5	12,778	10,186	7,948
	5.0	25,856	14,541	10,076
4.0	0.0	6,085	6,912	5,666
	2.5	9,155	8,500	6,755
	5.0	16,184	11,710	8,459

SOCIAL CAPITAL AND CATASTROPHIC RISK RESPONSES[1]

by

Lindon J. Robison and Steven D. Hanson[2]

Introduction

Decision makers sometimes face the possibility of an event which, if it occurs, has extremely unfortunate consequences. The possibility that such an event will occur is referred to as a catastrophic risk. When faced with a catastrophic risk, decision makers must determine: what are the options for altering either the likelihood or the outcome of the catastrophic event? If there exist options for altering the likelihood of the event or its outcome, then decision makers must determine: are the benefits of altering the catastrophic risk worth the cost?

Nearly all catastrophic and other risk studies by economists and other social scientists use the expected utility hypothesis (EUH). In most applications of the EUH, response to risk is assumed to depend on how the decision maker will personally be affected by risky events. This assumption of the EUH model is

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[1]This report draws heavily on a report prepared for Sandia National Laboratories. Their support for this research along with the Michigan Agricultural Experiment Station is gratefully acknowledged. This paper is identified as Michigan State University Agricultural Economics staff paper 93-27.

[2]Lindon J. Robison and Steven D. Hanson are professor and associate professor respectively in the department of agricultural economics at Michigan State University.

consistent with the neoclassical paradigm on which most economic reasoning is based; namely, that decision makers are motivated by selfishness of preferences.

The EUH paradigm is criticized because the basic assumption of selfishness of preferences underlying the paradigm is not tested. Thus, it is practically impossible in many cases to reject the theory because accommodating assumptions can nearly always be found to justify the observed behavior. Nevertheless, mounting evidence suggests that in many cases the underlying assumption of selfishness of preferences simply does not hold.

An alternative theory is referred to as social capital theory. Social capital theory suggests that benefits and costs of altering catastrophic risks depend on relationships between those affected by the risk as well as the standard self interest motive. Social capital theory does not argue that the neoclassical paradigm based on self interest is wrong, only that what constitutes the decision maker's self interest has been too narrowly defined or not well understood in most applications of the neoclassical paradigm. Recognizing that a decision maker's well being is not independent of the well being of others modifies the neoclassical paradigm to account for many of the observations that appear to refute the current theory.

In the remainder of this paper, we develop a model which incorporates social capital into a decision maker's catastrophic risk problem. The model is empirically tested using survey data from a hypothetical catastrophic risk situation. The empirical results support the hypothesis that social capital effects decision makers responses to catastrophic risk and thus suggest that modifications of the neoclassical theory need further consideration.

The Neoclassical Economic Approach

Implicit in the EUH model is the assumption that outcomes, usually income, is the decision maker's own income. Moreover, studies which attempt to estimate the risk aversion coefficients for individual utility functions typically measure how individuals respond to changes in the level and likelihood of having their own income altered (Young).

The focus on own income makes the EUH model consistent with the assumptions most often applied in the neoclassical economic paradigm. The assumptions underlying the neoclassical paradigm include: 1) that individual choices are motivated by self interest; and 2) that the identity of participants in the economic exchange do not affect the outcome.

Adam Smith, viewed as the founder of much of modern economics, seems to provide the basis for the selfishness of preference assumption when he wrote:

> An individual neither intends to promote the public interest, nor knows he is promoting it. ..He intends only his own gain, and he is led by an invisible hand to promote an end which was no part of his intention...

Challenges to the Neoclassical Paradigm

All economic models are only representations of the real world. Therefore any challenges to the neoclassical paradigm must do more than establish that the neoclassical paradigm or the EUH is an incomplete representation of a decision maker's response to risk. An alternative, or modification, of the neoclassical paradigm must define the conditions under which the neoclassical paradigm is not justified. Moreover, those who challenge the neoclassical paradigm must establish that models that ignore variables typically omitted from the neoclassical model, such as social bonds and decision maker values, are incapable of explaining important economic phenomenon that the neoclassical model claims to explain.

The selfishness of preference assumption underlying the neoclassical paradigm is particularly difficult to test. Sen (1977, p. 322) complains that: "It is possible to define a person's interest in such a way that no matter what he does can be seen as furthering his own interests in every isolated act of choice."

To illustrate Sen's concern, consider a soldier who falls on a live grenade to save his comrades. A neoclassical economist might explain such a phenomenon by saying: "the soldier had a taste for being blown up by a grenade" and was merely pursuing his self interest. On the other hand, for the soldier who avoided the "falling on the grenade assignment," his actions could also be explained by the self-interest motivation to avoid pain. Consequently, whatever the soldier's response to the possible catastrophe could be explained by a self-interested motivation. It is accommodations in the assumptions of what defines the soldiers' self interests that allow us to always confirm the neoclassical paradigm.

To avoid the tautology "that the soldiers did what they did because they wanted to do it," requires that we specify more carefully the soldiers' preferences. This requirement to say more about preferences, however, is exactly what modern neoclassical economists avoid.

Perhaps the most serious challenge to the neoclassical paradigm is that its predictive and descriptive value is being seriously challenged. Events it should predict are not being predicted well or are predicted with inconsistencies. Referring to the lack of consensus about the causes of economic development, G. E. Shuh, past president of the American Agricultural Economics Association wrote:

> Unfortunately, we do not yet have a theory of economic development, or even of agricultural development. What we have is a general consensus that the production and distribution of new production technology is a cheap source of income streams and thus must be the engine of economic growth at early stages of political and economic development.

Preference Evidence

In an effort to learn more about preferences and to test the assumptions underlying the neoclassical paradigm, Robison and Schmid asked students and faculty at Michigan State University:

"...what is the lowest price you would accept for your used car if the buyer were a close friend? a stranger? or a nasty neighbor?"

The conclusion from the survey was that individuals respond to how an event affects them personally (the price they receive), and by how an event affects significant others (the price significant others pay). In other words the survey results confirmed that in economic transactions, relationships matter.[3]

Other evidence of the public's awareness of the role of relationships making a difference in economic matters are nepotism laws. Nepotism laws impose restrictions on close relatives being hired by the government in the same agency. These laws recognize the tendency of government employers to grant advantages to their relatives. On the other hand, civil rights laws preclude employment being denied when the basis of the discrimination is race, a special kind of relationship. Our judicial system emphasizes the role of relationships. In our symbol of the court, lady justice wears a blindfold. The blindfold is intended to help her make impartial judgments free from the bias created if she could see who stood before the bar of justice. Then there are the individuals who purchase life insurance for the benefits they will never receive.

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[3]Clearly, after the fact, assumptions could be found that could reconcile self interests and the observed behavior. This approach, however, comes close to a tautological approach as already mentioned.

Finally, among those same economists who argue that relationships don't matter, reviews of articles submitted for publication consideration are conducted anonymously. That is, to insure impartial reviews, authorship is not revealed to reviewers of articles submitted to most professional journals. Unless interpersonal preferences influenced reviews, anonymity in the review process would be unnecessary (Blank).

Ignoring the role of relationships in most of economic and risk analysis may be excused if it accounts for only a small part of all economic activity. But this justification is easily refuted. Siles found, for example, that in a survey of 162 Michigan bankers that relationships mattered a great deal. He found that relationships between lenders and their loan customers did not alter by much the likelihood of a loan being approved for the very best or very worst customers. But among loan customers with questionable business strength as measured by profitability, liquidity, and managerial capability, relationships were very important.

Consistent with Siles' results are several Federal Reserve reports on home mortgage lending. They reveal that black and Hispanic applicants are denied credit at roughly twice the rate of white applicants even when the white and black and Hispanic applicants are statistically similarly qualified (Avery, Beeson, and Sniderman).

Relationships in the job market are also crucial. According to a U.S. Bureau of Labor study, 63.4 percent of the jobs are a result of informal contacts where the job seekers exercise their own initiative in building on personal contacts.

Not easily explained by selfishness of preferences are charitable donations. Despite a sluggish economy, philanthropic giving across the nation increased in 1991 over 1990 by 6.2 percent to $124.7 billion. According to the Trust for Philanthropy, the American Association of Fund-Raising Counsel's research arm, 89 percent of the amount contributed was by individuals. Largest recipients included religious organization, $67.6 billion, and education, $13.3 billion. Other recipients included environmental groups, the arts, health organizations, and other nonprofit groups providing human services (Tetsch).

Finally, according to a U.S. Census study, 80 million Americans volunteered an average of 4.7 hours per week in 1987 or 19.5 billion hours. Unless there can be found a taste for giving away one's money and time, billions of dollars worth of economic activity in the U.S. economy is largely unaccounted for by the selfishness of preference assumption.[4]

Socio-Economics and Social Capital Theory

Despite evidence that it often fails to predict or explain economic behavior, the neoclassical paradigm must remain unchallenged unless an acceptable alternative is available. An

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[4]We do not deny that selfish motives can be devised to explain charitable donations such as giving to a religion in hopes of a better position in the next life. But since assumptions themselves are not tested, there is no reason to not consider other explanations for charitable giving.

alternative view is loosely represented by the emerging economic subdiscipline of socio-economics. According to socio-economists, individual choices are shaped by values, emotions, social bonds, and judgements, rather than by a precise calculation of self-interest (Coughlin).

A recent and popular example of a socio-economic model is Etzioni's. The basis of Etzioni's model is that there exists within individuals two sometimes conflicting motives: self interest urges and values about what is right and wrong. While one of the selves may indeed pursue selfish pleasures, the other self evaluates the actions. The result is often a conflict. Etzioni (1991) illustrates this internal conflict with the simple statement: "I would <u>like</u> to go to a movie, but I <u>ought</u> to visit my friend in the hospital."

Social capital theory, an alternative proposed in this paper, maintains the assumption that individuals pursue their self interest. It differs from the neoclassical model in that it more broadly defines the set of events that increase one's sense of well being.

Elements of Social Capital Theory

Fundamental to social capital theory is the view that self-interested individuals are capable of vicariously sensing the well-being of others. As a result of this vicarious sensing ability, changes in the well being of significant others may affect an individual even though the individual may not be directly affected.

The social capital model also recognizes that individuals do not experience the well being of others equally. This ordering leaves individuals most sensitive to the well being of persons, places, or things with which they are most alike, with whom they have made commitments and assumed responsibility, or with those with whom they have significant emotional and social ties.

Adam Smith recognized a social weighting scheme of vicarious sensing like the one proposed here when he wrote:

> Every man feels his own pleasures and his own pains more sensibly than those of other people...After himself, the members of his own family, those who usually live in the same house with him, his parents, his children, his brothers and sisters, are naturally the objects of his warmest affection.

<u>Social Distance</u>

The underlying assumption that relationships matter depending on some social distance metric has long been recognized by sociologists. Park considers the concept of "distance" to mean the grades and degrees of understanding and intimacy that characterize personal and social relations. Expressions such as A is close to B but C is distant and reserved or that D is open-minded, sympathetic, understanding, and generally "easy to meet," all reflect the notion of social distance.[5] In the context of what we propose as social capital theory, Park's social distance appears to combine elements of both relationships and awareness.

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[5]Park, R. E. "The Concept of Social Distance." <u>Journal of Applied Sociology</u>. 8(1924):339-344.

A synonym for a positive relationship is social capital or cohesion. Cohesion is a positive expressive relationship between two or more persons. Said another way, cohesion is indicative of the bonding of individual i to person j. From the social capital theory perspective, cohesion presupposes awareness and usually assumes a positive relationship.

<u>Relationships</u>

Bogardus defines three grades of understanding and intimacy among races and individuals: 1) friendly feelings, 2) feelings of neutrality, and 3) feelings of antipathy. Personal friends and acquaintances in one's own "universe of discourse" are examples of the first type. In the second group are those of different racial or ethnic backgrounds. And in the third group are those towards whom one feels disgust or dislike.

Bogardus tries to develop a "social distance scale" based on a person's relationships to other individuals and organizations. Underlying his scale is the basic concept that the more prejudiced an individual is against a particular group, the less the person will wish to interact with members of the group. Bogardus, like Etzioni, presupposes in his discussion an awareness that permits a relationship to develop that depends on the differences that i perceives between himself or herself and person, place, or thing j.

As the writings of Bogardus, Park and others indicate, the study of relationships has long attracted the interest of sociologists and others. Integrating recognized concepts of relationships into economic models has not been seriously attempted.

A Social Capital Decision Model

The previous sections have argued that relationships can influence economic choices. In this section a model is developed which incorporates relationships into the decision problem of an agent facing catastrophic risk.

Let the ith agent's utility be represented as $U_i(\pi_i, K_{ij}\pi_j)$ where U_i is a concave von Neumann-Morgenstern utility function; π_i and π_j are the ith and jth agents' wealth (material and physical capital), and K_{ij} represents the social capital possessed by agent i for agent j.

Social Capital K_{ij} is a function of relationships and social distance coefficients and represents what person i feels towards person, place or thing j. The relationship i feels towards j may be sympathetic, neutral, or antipathetic producing corresponding social capital coefficients that are positive, zero, or negative. The social distance between i and j from i's perspective ranges between no awareness to socially close. Corresponding social distance coefficients range from zero to one.

For simplicity, π_i and π_j are assumed to be deterministic in the absence of catastrophic risk so that they represents a known constant. In the absence of catastrophic risk, agent i's decision problem becomes: Max $U_i(\pi_i, K_{ij}\pi_j)$ for some decision vector

x. It is important to note that in general the choice of x can affect π_i, K_{ij}, and π_j.

In the empirical section of the paper we study the effects of catastrophic risk on the decision process for three alternative situations. We begin by establishing a base solution in which the decision maker is asked to take a catastrophic risk that makes π_i stochastic such that $\tilde{\pi}_i=\pi_i+y$ where $y\leq 0$ is a random variable, one value of which is zero if the catastrophe does not occur.

In the base solution, each agent is asked what percentage increase in his or her deterministic salary, $\delta_1\pi_i$, would be required to undertake the catastrophic risk and be indifferent to their original condition without the driving risk? This equilibrium level of salary increase δ_1 is expressed as:

(1) $E_iU_i(\tilde{\pi}+\delta_1\pi_i, K^1_{ij}\pi_j)=U_i(\pi_i, K^1_{ij}\pi_j)$

where E_i is the expectations operator given i's perceptions of the probability of catastrophic outcomes. In this case $\delta_1\pi_i$ is a form of certainty equivalent income which makes i equally happy in the presence of the catastrophic risk as he or she was in its absence.

Next the decision problem is altered so that agent j forces agent i to undertake the catastrophic risk. In the base solution, j gave i the choice of accepting the risk with compensation or not taking the risk. In this case j insists i undertake the risk and by so doing one would expect that K_{ij}

would be reduced, i.e. $K_{ij}^2\pi_j<K_{ij}^1\pi_j$. Agent i is again asked what level of compensation, $\delta_2\pi_i$, he or she would require to be as well off as without the risky assignment. As before, i's decision problem can be written as:

(2) $E_iU_i(\bar{\pi}_i+\delta_2\pi_i, K_{ij}^2\pi_j)=U_i(\pi_i, K_{ij}^1\pi_j)$

Because of the reduced value of K_{ij}^2 relative to K_{ij}^1 in equation (1), we expect $\delta_2>\delta_1$. Thus when the relationship is changed (made worse) by not having the alternative of refusing the risk, the decision maker requires more certain income to be returned to indifference.

Finally, the decision problem is altered such that agent i is offered the option of undertaking the catastrophic risk with compensation as in the base solution. However, in this case if i refuses to undertake the risk, then agent j will be required to accept the risk. Again each agent is asked to determine the compensation level $\delta_3\pi_i$ such that he or she is equally as well off with or without the catastrophic risk.

Formally, agent i chooses δ_3 such that:

(3) $E_iU_i(\bar{\pi}_i+\delta_3\pi_i, K_{ij}^3\pi_j)=E_jU_i(\pi_i, K_{ij}^3\bar{\pi}_j)$

As long as K_{ij}^3 in equation (3) is positive, $E_jU_i(\pi_i, K_{ij}^3\bar{\pi}_j)<U_i(\pi_i, K_{ij}^3\pi_j)$ requiring that $\delta_3>\delta_1$.[6] If K_{ij} is negative, then $\delta_3<\delta_1$. In addition, as K_{ij}^3 increases, so will the value of δ_3. The economic implications of this result are

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[6]This assumes that K_{ij} is not altered by the presence of the catastrophic risk itself.

significant. Individuals decisions that affects others will alter the choices of decision makers depending on their social capital. The results above if confirmed suggest that responses to risk must be examined in a broader context than economists have used in the past.

The Survey

A survey was used to collect data needed to test if relationships affected the costs of bearing catastrophic risk according to the predictions of the social capital model developed in the previous section.

The survey was designed to measure the effect on risk taking due to social bonds and values separate from other self interest motives. For example, forming social bonds may allow individuals to gather information that reduces transaction costs. Therefore, a decision apparently made to strengthen social bonds may be motivated by the selfish desire to reduce transaction costs. In the context of this study it is useful to design questions whose answers reflect the role of social capital.

A second survey criteria was to identify a catastrophic risk context in which survey respondents could respond to with familiarity and realism. The probability of a car accident is a risk that most individuals have considered and to which they have responded. To utilize the familiarity of catastrophic risks associated with car accidents, the survey document designed questions associated with responses to possible car accidents.

Questions about the risk of car accidents provides an identifiable catastrophic risk to which survey respondents can answer with some degree of familiarity and realism.

The respondents to the survey were 60 graduate students enrolled in the department of agricultural economics at Michigan State University. Most of the students surveyed had work experience in which a driving assignment was a possibility.

The first question described a work assignment that involves driving. If one accepts the assignment, then included with the driving assignment is the risk of an accident. Respondents were asked what percentage increase in base salary would leave them indifferent between the status quo and accepting the driving assignment. In other words, the respondents are asked to provide δ_1.

Next the respondents are told they must accept the driving assignment. This request or demand is assumed to change the relationship between i and j from what it was in the first question. Respondents were again asked for the percentage increase in the base salary required for them to be indifferent between the status quo and accepting the driving assignment. Their responses allowed us to determine the value of δ_2.

These questions measure the effect on the required compensations of a changed relationship between the employee and the employer. The null hypothesis suggests that the changed relationship should not affect the willingness to bear risk. This hypothesis is consistent with the neoclassical view. The rejection of the null hypothesis would support the socio-economic view that relationships do matter.

Finally, respondents are told to assume that if they do not accept the driving assignment that j, a close personal friend, a stranger, or an unpleasant co-worker, will be required to accept the assignment without any increased compensation. The intent was to test if varying K_{ij} produced results consistent with social capital theory. In other words does δ_3 decreases as K_{ij} increases?

The results of the survey are summarized in Table 1. Columns (1) and (2) report average response to the survey of all respondents. The difference between columns (1) and (2) reflect differences in the probability of being involved in a fatal accident. Column (1) reflects the response to risk when the probability of a fatal accident is .01%. Column (2) reflects the response to risk when the probability of a fatal accident is .001%.

Differences in risk produced the most response when there were no external consequences for i as a result of refusing the risk and when a close friend would be assigned the risk if i refused to drive.

Requiring respondents to accept the risk yet compensating them for the increase in risk did not change significantly the amount of compensation required. That is, δ_1 was not statistically different from δ_2. Apparently, requiring the employee to accept the risk with compensation did not change the social capital coefficient K_{ij}.

Table 1. Percentage increase in salary required for indifference to accepting a new risk:

Catastrophic risk choices		Prob. of Catastrophic Risk for All Respondents .01%	.001%
		------percents----	
		(1)	(2)
A.	No external consequences (δ_1)	11.5	9.6
B.	No option to refuse (δ_2)	11.2	10.4
C.1	Refusal leaves uncompensated risk to close friend (δ_3;K^3_{ij}>0)	8.4	7.5
C.2	Refusal leaves uncompensated risk to stranger (δ_3;K^3_{ij}=0)	11.7	11.1
C.3	Refusal leaves uncompensated risk to unpleasant co-worker (δ_3;K^3_{ij}<0)	13.2	13.0

The indifference level of compensation did depend on who would have the risk if i refused it. If refusal meant a close friend must accept the risk, then avoiding the risk was less valued compared to the no external consequence case, i.e. $\delta_3<\delta_1$. If the driving requirement were expected of stranger, then the consequences were not considered significantly different than the no external consequence case, i.e. $\delta_3=\delta_1$. Finally, if the consequence of refusal was an unpleasant co-worker would be given the driving assignment, then the satisfaction of not driving was very high and required the largest of all risk premiums to induce i to drive, i.e. $\delta_3>\delta_1$. These results support the hypothesis that δ_3 increases as K^3_{ij} increases.

The most significant response to the questionnaire was when refusal to drive imposed the driving assignment on a close friend. When confronted with the possibility that their refusal of the risk would leave it to a close friend who would not be compensated, the indifference level of salary for all respondents decreased from 11.5% to 8.4% and from 9.6% to 7.5% at the .01% and .001% level of risk respectively. In other words, the respondents would require a significantly smaller salary increase to return them to indifference if the consequence of their not accepting the risk would be that their friends would have to accept the risk.

Another pronounced effect of the survey was the increase in compensation over the no external consequence case was when an unpleasant co-worker would be required to bear the risk. For all respondents it increased from 11.5% to 13.2% and from 9.6% to 13.0% for risk at the .01% and .001% respectively.

These results support the general conclusions of social capital theory: relationships matter. Consistent with the conclusion that relationships matter are the results supported by this study that indicate individuals make decisions in part in response to how their decisions will affect others.

Characteristics Influencing Risk Responses

Individual responses to risk may depend on other respondent characteristics in addition to relationships. For example, different responses to risk may exist between men and women. Or differences in driving skills may account for part of the differences in responses to the questions. In order to isolate differences due to social capital coefficients independent of other influences, the survey asked questions about the respondents that allowed for differences unrelated to social capital to be accounted for separately from the influence of social capital.

To control for differences between respondents, information was collected about their age, income level (lower, middle, upper middle, and upper), education level, number of dependents, level of driving skills, miles normally driven per year, the extent of seat belt use, past involvement in an accident, amount of life insurance carried, citizenship, strength of religious beliefs, and sex.

The responses were then analyzed using tobit analysis. Tobit analysis is a procedure similar to ordinary least squares that allows for the analysis of bounded continuous variables (Green). The results of the tobit analysis are reported in Table 2.

Table 2. Tobit Analysis of Characteristics Explaining Respondents Response to Risk.

Variable	Coef.	T-Stat.	2-Tail Sign.
Constant	9.53	9.94	.00
Forced assign.	1.40	1.82	.07
Risk (.001=1)	-.87	-1.53	.13
Miles driven per year	-.0003	-6.00	.00
Sex (male=1)	-2.26	-4.06	.00
Excellent Driving Skills	1.32	1.92	.05
Ave. Driving Skills	1.58	.85	.40
Small Life Insurance	2.00	2.93	.00
Large Life Insurance	-5.96	-3.63	.00
Close Friend	-2.64	-3.38	.00
Unpl. Coworker	1.23	1.54	.12
R-squared	.19	Mean of dep. var.	6.54
Number of observations:	543		

The constant term in table 2 measures the amount of compensation the respondent would require to accept the driving assignment and be indifferent under the following conditions: (1) if the risk of a fatal accident were .01%; (2) if a stranger will be required to absorb the risk if the respondent refuses; (3) if the respondent has average driving skills; (4) if the respondent carries a moderate amount of life insurance; and (5) if the respondent were female.

The other coefficients in table 2 measure adjustments to the constant term or base case. For example, the risk coefficient in table 2 indicates that the compensation level recorded by the constant term will fall by .87 percent if risk is reduce from .01 to .001 percent.

The close friend coefficient indicates the change in compensation that would be required for indifference if the risk were passed on to a close friend instead of a stranger. Under this assumption, the compensation required for indifference would decrease by 2.64 percent from that required if the stranger were to assume the risk. And if an unpleasant co-worker were required to assume the risk if refused by the respondent, then the compensation required increased on average of 1.23%. However, the statistical significance of this coefficient is weak.

Other variables statistically significant in explaining the level of compensation include the level of driving skills, miles driven per year, past involvement in an accident, life insurance coverage, and sex of the respondent.

Those who indicated good driving skills required more compensation that those with poor driving skills. They may have believed that better driving skills deserved better than average reimbursement.

The more miles driven per year the less compensation was required. Those that carried small or no life insurance required additional risk premiums while those who carried large amounts of life insurance were willing to reduce their compensations requests by almost 6%. Finally males required on average 2.6% lower percentage increases in salary than did females.

Conclusions

This paper has asked the question: how do relationships affect the willingness to face catastrophic risks? The report challenges the existing framework of risk analysis, the neoclassical EUH, because it fails to account for how risk affects others that have a significant relationship with the decision maker. This paper utilizes social capital theory to develop an EUH model that accounts for the effect of relationships on willingness to accept catastrophic risk.

The model is then tested using data collected from a survey administered to 60 graduate students at Michigan State University. The empirical results support the implications of the social capital version of the EUH model. An individual's willingness to bear risk and to impose costs on others to alter risk depends on relationships.

For policy makers the results of this study are important. Weapons systems, nuclear power plants, hazardous chemicals, and other features of our modern world subject individuals to risk.

The trade offs between individual's willingness to bear risk depends on who directly bears risk as well as the relationships to those who bear risks.

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Bootstrapping Discrete Markovian Transition Probabilities with Complete and Reduced Sets of State Variables

by

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Bootstrapping Discrete Markovian Transition Probabilities with Complete and Reduced Sets of State Variables

Empirically implementing a discrete stochastic dynamic programming (SDP) study requires that the researcher choose the appropriate number of state variables as well as estimate the model's parameters and state transition probabilities. The number of state variables will be partially determined by the structure of the model and by the nature of the econometric models used to estimate the model's parameters and transition probabilities. The number of state variables as well as the joint estimation of the state transition probabilities and the parameters introduce several complexities into the process. In this paper we discuss two such complexities: (1) that the functional form as well as the parameters of the conditional transition probabilities are usually unknown and must be assumed or estimated, and (2) that the econometric model, which best predicts the state transitions, may contain a set of state variables too large to be practically included in the SDP model. The latter problem is commonly referred to as Bellman's "curse of dimensionality."

The fact that the functional form and the parameters of the state transition probabilities are usually unknown is not unique to the construction of SDP models. The functional form of the error structure is usually unknown in most econometric studies. It is common to assume normally distributed errors, especially if two or more correlated random variables must be predicted simultaneously. The assumption of normally distributed errors is usually one of convenience and cannot always be justified by an appeal to the central limit theorem. (An example of a situation where yield distributions were not normally distributed can be found in Day.) Recognizing the possibility of non-normal errors, some authors have suggested fitting flexible functions to the residuals of the regression (see Taylor or Burt and Taylor). Taylor used maximum likelihood procedures to estimate the parameters of a flexible functional form and reported generally good results with univariate errors. Whether or not the procedure could be practically extended to multivariate error distributions is not clear.

Applied researchers often find themselves in a type of information dilemma when constructing the SDP model. The best fitting econometric model may exacerbate Bellman's "curse of dimensionality." Often the researcher must compromise by discarding some state variables to obtain a computationally feasible model. Burt, and Burt and Taylor discuss procedures to reduce the number of state variables and to obtain conditional forecast error distributions with reduced information. Burt and Taylor's approach is applicable to situations where forecasts are constructed using difference equations with lagged variables as state variables and when the evolution of the state variables is not influenced by the decision maker's actions. They present statistics which quantify the relative amount of information discarded in the state variable truncation process.

Burt and Taylor's procedure is useful but becomes somewhat mathematically tedious with increased numbers of lagged variables or with a non-normal error structure. Burt and Taylor's procedure also assumes that parameter values are known and requires that the error structure be estimated using a known (perhaps non-normal and/or multivariate) functional form. Their procedure exploits symmetry in the time series and is not applicable when the time series is not symmetric.

This paper demonstrates that an alternative procedure known as bootstrapping (Efron) can be used to provide robust estimates of conditional transitional probabilities. The robustness of the procedure is especially useful when the researcher does not know the functional form of the transition distribution. Additionally, we show that bootstrapping and simulation procedures can be combined to estimate state transition probabilities when information is intentionally discarded so as to reduce the number of state variables in the SDP problem.

The paper is organized in the following manner. We first present a brief overview of the bootstrapping literature. Procedures which allow the conditional transition probabilities to be estimated are discussed. The results of several Monte Carlo studies which examine the accuracy of estimated transition probabilities are presented. The results of the Monte Carlo studies indicate that one period ahead "full state variable" bootstrap estimates are almost as efficient as those using the known functional form of the distribution with statistically estimated parameters. Additionally, the bootstrap procedure is robust to changes in the underlying functional form of the distribution. These results hold for both the univariate and multivariate cases examined. Finally, distribution estimates for the reduced state variable models are shown to be surprisingly accurate although, as expected, the precision of the distribution estimates declines when information is discarded.

A Brief Overview of Bootstrapping

Efron first presented the bootstrapping approach as a procedure to examine properties of statistics whose sampling characteristics were mathematically difficult or intractable. He demonstrated that bootstrapping was useful in examining the characteristics of a number of sample statistics including the variance of the sample median and estimated regression parameters. Efron and Gong further examine bias in parameter estimates and small sample variance of parameter estimates. Freedman discusses the usefulness of bootstrapping through the statistical properties of least squares parameter estimates. Bickel and Freedman present asymptotic results and situations in which bootstrapping procedures would fail. Freedman and Peters report the results of a Monte Carlo study examining the properties of generalized least squares estimates. They report that "the conventional asymptotic formulas for estimating standard errors are too optimistic by factors of nearly three" with their problem. Veall's IER article and Bernard and Veall develop estimates of future electricity demand. Veall demonstrates that bootstrapped estimates of confidence intervals are broader than those obtained using traditional methods. Bernard and Veall estimate the distribution of future electricity demand with serially correlated errors and random independent variables.

Veall (1987-#2) reports the results of a Monte Carlo study examining the accuracy of bootstrapped forecast distributions. In the study, he generates samples from a known (normal) power demand distribution. He then measures how well the bootstrapped estimates of the future power demand distribution fit the known distribution. His results indicate that the bootstrap was remarkably accurate in estimating the upper tail of the probability distribution. The lower tail did not fit as well, which led Veall to advise caution in using the bootstrap in other situations. However, as will be seen later in this paper, Veall's pessimism may be premature. We show that traditional procedures for estimating the tails of forecast distributions generate root mean squared estimated quantile errors that are almost as large as the bootstrapped quantile estimate. This result is particularly interesting in our first and third cases where the researcher is assumed to know the correct functional form of the error distribution.

Prescott and Stengos demonstrate the use of the bootstrap procedure and use it to forecast U.S. pork supplies. They report the results of a Monte Carlo study examining the accuracy and dispersion of parameter estimates and confidence intervals as well as the effects of introducing additional stochastic variables into the forecasting exercise.

The above studies demonstrate the usefulness of bootstrapping with fully specified models. However, they do not directly contrast bootstrapped distribution estimates to those obtained with traditional procedures. Nor do they examine the robustness of estimated forecast distributions to changes in the underlying error distribution. Finally, no previous study has examined the potential usefulness of bootstrapping in estimating the transition probabilities of models with reduced state variables. The next section of the paper describes the procedures used in this paper to examine the robustness of estimated transition distributions with complete and reduced sets of state variables.

Bootstrapping Procedures with Complete and Reduced Sets of State Variables

The following section describes the models and procedures used in the Monte Carlo studies. Before proceeding, a brief discussion of bootstrapping forecast errors would be helpful. For this description we borrow heavily from Prescott and Stengos.

Bootstrapping with Complete State Variables.

Assume that the researcher believes a second order linear stochastic difference equation adequately describes the evolution of the variable y_t, i.e.,

(1) $$y_t = a_0 + a_1 y_{t-1} + a_2 y_{t-2} + e_t$$

where $a = [a_0, a_1, a_2]'$ is a vector of unknown parameters and e_t is an i.i.d. disturbance with an unknown distribution.[1] It is assumed that the researcher has a finite sample of y_t observations ($t=-1,0,1,2, \ldots T$), which will be used to estimate the parameters $\underline{a}$ and the error structure. Bootstrapping the one period ahead forecast distribution proceeds as follows:

a) Obtain statistical estimates $\underline{\hat{a}} \in R^3$ and $\underline{\hat{e}} \in R^T$ using the original data. Retain the values y_{-1} and y_0 to reconstruct the bootstrap "artificial samples."

b) Resample from $\underline{\hat{e}}$ to obtain e_t^j ($t = 1,2, \ldots T$, $j=1,2, \ldots J$) where e_t^j is randomly drawn (with replacement) from the original estimated residuals $\underline{\hat{e}}$, and J is the desired number of bootstrap replications.

[1] The assumption that e_t is i.i.d. is made for convenience only. The error structure could be AR(p), MA(q), or ARMA (p,q). However, the bootstrapping procedure used here requires that the error structure have an i.i.d. component that can be resampled to reconstruct the time series.

c) Using the original parameter estimates, $\underline{\hat{a}}$, the resampled errors, $\underline{e}^j$, as well as y_{-1} and y_0, recursively reconstruct an artificial sample vector $\underline{\tilde{y}}^j$ as

(2) $$\tilde{y}_t^j = \hat{a}_0 + \hat{a}_1\tilde{y}_{t-1}^j + \hat{a}_2\tilde{y}_{t-2}^j + e_t^j \qquad \text{(for } t = 1, 2, \ldots T \text{ and } j = 1, 2, \ldots J\text{).}$$

d) Using $\underline{\tilde{y}}^j$, re-estimate the parameters $\underline{\hat{a}}^j$ and the residuals $\underline{\hat{e}}^j$ ($j=1,2,\ldots J$) using the same procedures used in step (a).

Given the original parameters, $\underline{\hat{a}}$, the forecast $\hat{y}_{T+1}$ conditional on y_T and y_{T-1} is:

(3) $$\hat{y}_{T+1} = \hat{a}_0 + \hat{a}_1 y_T + \hat{a}_2 y_{T-1}.$$

More than one procedure exists to bootstrap the conditional forecast error distribution. We examine two of these procedures which we call the Prescott-Stengos (P-S) procedure and the residual bootstrap (R-B) procedure, respectively. The Prescott-Stengos (P-S) procedure simulates the forecast error as

(4) $$fe_{T+1}^j = \tilde{y}_{T+1}^j - \hat{y}_{T+1}^j \qquad (j=1,2,\ldots J)$$

where

(5) $$\tilde{y}_{T+1}^j = \hat{a}_0 + \hat{a}_1 y_T + \hat{a}_2 y_{T-1} + e_{T+1}^j$$

and

(6) $$\hat{y}_{T+1}^j = \hat{a}_0^j + \hat{a}_1^j y_T + \hat{a}_2^j y_{T-1}.$$

In expression (5), e_{T+1}^j, is resampled with replacement from the original residual estimates. Given the results of expressions (3) through (6), the discrete (P-S) bootstrap estimation of the state transition evolution is:

(7) $$y_{T+1}^j = \hat{y}_{T+1} + fe_{T+1}^j$$

with

(8) $$\Pr\left(y_{T+1} = y^{j}_{T+1} \mid y_T, y_{T-1}\right) = 1/J \qquad \text{(for } j = 1,2,\ldots J).$$

In (8) $\Pr(\cdot \mid \cdot\cdot)$ is the bootstrapped probability of event $(\cdot)$ conditional on event $(\cdot\cdot)$. The estimated state transition evolution of y^{j}_{T+1} can also be written as [by substituting expressions (3) through (6) into (7)]:

(9) $$y^{j}_{T+1} = \left(2\hat{a}_0 - \hat{a}^{j}_0\right) + \left(2\hat{a}_1 - \hat{a}^{j}_1\right)y_T + \left(2\hat{a}_2 - \hat{a}^{j}_2\right)y_{T-1} + \hat{e}^{j}_{T+1}.$$

This version will proves useful in discussing the simulation procedures used to estimate the state transition probabilities with reduced state variables.

The residual bootstrap procedure simulates the conditional forecasting errors as:

(10) $$FE^{t,j}_{T+1} = \hat{e}^{j}_{t} \qquad (t=1,2,\ldots T, \text{ and } j=1,2,\ldots J)$$

where $\hat{e}^{j}_{t}$ is the t[th] element of the i.i.d. bootstrapped residual vector $\underline{\hat{e}}^{j}$. The R-B estimation of the state transition evolution is:

(11) $$y^{t,j}_{T+1} = \hat{y}_{T+1} + FE^{t,j}_{T+1}$$

with

(12) $$\Pr\left(y_{T+1} = y^{t,j}_{T+1} \mid y_T y_{T+1}\right) = 1/(T \cdot J) \qquad (t=1,\ldots T,\ j=1,\ldots J).$$

With numeric stochastic dynamic programming models, it is common to break the range of possible y_t values into discrete intervals or cells. In the following, it is assumed that the researcher wishes to estimate the Markovian probability of moving to a particular cell k of y_{T+1} conditional on y_T, y_{T-1} being in cells l and m respectively. We denote this probability as $\Pr\left({}_k y_{T+1} \mid {}_l y_T, {}_m y_{T-1}\right)$. Given that y_T is in cell l and y_{T-1} is in cell m, let the number of times that y^{j}_{T+1} [from (9) or (12)] is in cell k be ${}_kN_{l,m}$. The condition probability of y_{T+1} moving to cell k is then

(13) $$\Pr({}_k y_{T+1} \mid {}_l y_T, {}_m y_{T-1}) = {}_kN_{l,m}/J \qquad \text{or} \qquad {}_kN_{l,m}/(T\cdot J).$$

Bootstrapping Reduced Sets of State Variables

The previous section discussed bootstrapping transition probabilities with the complete set of state variables, i.e., y_T, y_{T-1}. We now wish to reduce the state variables to y_T and estimate

(14) $\Pr({}_k y_{T+1} \mid {}_l y_T)$.

Burt and Taylor discuss the difficulties in accurately estimating the probabilities with reduced state variables. Probability theory gives:

$$(15) \qquad \Pr({}_k y_{T+1} \mid {}_l y_T) = \frac{\sum_m \Pr({}_k y_{T+1} \mid {}_l y_T, {}_m y_{T-1}) \Pr({}_l y_T, {}_m y_{T-1})}{\sum_k \sum_m \Pr({}_k y_{T+1} \mid {}_l y_T, {}_m y_{T-1}) \Pr({}_l y_T, {}_m y_{T-1})}.$$

The values of $\Pr({}_k y_{T+1} \mid {}_l y_T, {}_m y_{T-1})$ have been previously identified. How does one obtain $\Pr({}_l y_T, {}_m y_{T-1})$, the joint probability that y_T is in cell l and y_{T-1} is in cell m?

Burt and Taylor present an exact method which requires the construction and inversion of a potentially large dimensioned Markov matrix. (If the range on y_t was divided into 100 cells, the Markov matrix for the second order difference equation would have 100^2 rows and columns. For the four state variable model discussed later, the markov matrix would have 100^4 rows and columns.) With increased numbers of state variables the exact procedure becomes burdensome or the range of the state variable must be broken into a smaller number of cells with the resulting DP solutions being more coarsely approximated.

We propose an alternative procedure in which the desired probabilities can be estimated using simulation procedures. Given $\underline{\hat{a}}$, e^{j}_{T+1}, $\underline{\hat{a}}^j$, and $\underline{\hat{e}}^j$, we simulate the evolution of y_t for a large number of time periods. The P-S evolution of y_t conditional on y_{t-1} and y_{t-2} is simulated by randomly drawing $j \in \{1,2,\ldots J\}$ and using expression (9). The R-B evolution of y_t conditional on y_{t-1} and y_{t-2} is simulated by randomly drawing $t \in \{1,2,\ldots T\}$ and $j \in \{1,2,\ldots J\}$ and using expression

(11). As we proceed, we record the number of transitions from state to state and bypass the Bayesian calculations in expression (15) altogether. The simulation procedure is less precise than the exact procedure in estimating the transitions form low probability states. However, the low probability of being in such states will usually result in the reduced precision having little or no influence upon the optimal SDP policy.

The Monte Carlo Studies

A number of Monte Carlo studies were conducted to examine the accuracy of the conventional and bootstrap methods in estimating conditional transition probabilities. We report the results of three studies here. All three of the reported studies use parameters estimated from the USDA land price series for North Central Iowa. The first study consists of a second order difference equation of land prices with a normally distributed error process. The second study consists of a second order difference equation with a zero centered gamma error distribution. The third study consists of a recursive pair of equations with land price forecasts conditional on lagged cash rent and land price state variables.[2] In the third study, land prices are normally distributed but are assumed to evolve as the weighted sum of two independent normally distributed random variables. For each of the Monte Carlo studies the actual conditional quantiles are known for the complete state variables models and the truncated second order process with normal disturbances. The actual conditional quantiles for the truncated Gamma model and the land price models were estimated using a 1,000,000 and 2,000,000 period simulation, respectively.

In each case, 500 samples of length 25 were generated with predetermined parameters. For each sample, parameter estimates were obtained. Conventional quantile estimates were constructed

[2] In each case, parameter estimates were constrained so as to lie within the stationarity triangle.

using the estimated parameters and assuming normally distributed errors. For each of the 500 samples, 400 bootstraps were estimated and a 100,000 period simulation completed.[3] The 400 bootstraps were used to construct quantile estimates for the complete state variable models. The 100,000 period simulation was used to estimate the reduced state conditional quantiles. The estimated quantiles were used to calculate the mean estimated quantile error and the root mean squared estimated quantile error. The results of the three studies are presented in Tables 1 through 3.

A Second Order Difference Equation with Normal Disturbances

The first Monte Carlo study examined the second order difference equation:

$$y_t = 215.89 + 1.679y_{t-1} - .774y_{t-2} + e_t \tag{16}$$

with $e_t \sim$ Normal (0,225). Table 1 presents the quantiles the mean quantile estimation errors, and the root mean squared quantile estimation errors (in parentheses). The results for the complete two state variable model are in columns 2 through 5 with the results for reduced one state variable model in columns 6 through 9. The two state quantiles for y_{T+1} are conditional on $y_T = y_{T-1} = 2{,}265$, while the one state quantiles are conditional on $y_T = 2{,}265$.

Columns 3, 4, and 5 contrast the accuracy of the conventional complete state variable quantile estimation procedure with the nonparametric bootstrapped quantile estimates.[4] The bootstrapped quantile estimates are almost as accurate as those obtained with conventional procedures and a correctly assumed functional form. The complete state variable P-S bootstrap procedure generates

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[3] A 200,000 period simulation was used for the four state variable land price model so as to obtain a sufficient number of observations in cells R_T and V_T.

[4] The traditional procedure used here assumes that the one period ahead error distribution is normally distributed with mean zero and an unknown standard error. From sample to sample, the standard error is assumed to equal the standard error of the estimate obtained from the regression.

quantile estimates that have a lower root mean squared quantile estimation error than those generated by the traditional procedure for the 10 to 90% quantiles. The P-S bootstrapped estimates are slightly more biased than those generated with the traditional procedures. In every case, (with the complete set of state variables), the P-S procedure generates slightly lower root mean squared quantile estimation errors than those generated with the R-B procedure. It appears that if the researcher knows that the error distribution is indeed normal and can retain two state variables, the P-S procedure is slightly preferred over the R-B procedure. Our one period ahead results differ from Veall's several period ahead results in that the bootstrap estimates estimated the lower half of the distribution as accurately as the upper half of the distribution. The results indicate that Veall's caution about the usefulness of bootstrapping in estimating out of sample forecast distributions may be premature when the alternative is to construct conventional forecasts with estimated parameters. In both cases, the estimated quantiles will often vary from the true quantile levels with the estimates of the distribution tails being less precise than those around the mean of the process.

Columns 6 through 9 list the quantiles for the one state variable model and contrast quantile estimates obtained with Burt and Taylor's exact procedure (assuming normality and using estimated parameters) with those obtained with bootstrap simulations. In this case, the nonparametric bootstrapped quantile estimates are more accurate than those obtained when using estimated parameters with a correctly assumed functional form for the error distribution.[5] When only one state variable is retained the R-B bootstrap procedure generates lower root mean squared estimation errors than the P-S procedure for all quantiles except the 50% quantile.

In the first example, the researcher accurately assumed that the error structure was normal. In practice, the functional form of the error structure is not known and may be incorrectly assumed

[5] Accurate, in the sense of having lower root mean squared estimation errors.

to be normal. Such a possibility is examined in the second Monte Carlo study discussed in the next section.

A Second Order Difference Equation with a Zero Centered Gamma Disturbance

The second Monte Carlo study examined the robustness of the bootstrapping procedure using difference equation (16) but with $e_t \sim$ [Gamma (6, 91.86) − 551.16]. Subtracting 551.16 centers the error disturbance at zero while maintaining a standard error of 225 — equal to the standard error in the first study.[6] The Gamma(6, 551.16) distribution is positively skewed but "normal looking" enough that most samples of size 25 generated with it are not rejected as normal with several common statistical tests of normality. This result might lead the researcher to mistakenly assume that the disturbance term is normal.

Table 2 presents the results of the Monte Carlo study. The complete state model's quantile values, mean estimated quantile errors and root mean squared quantile estimation errors are presented in columns 2 through 5. The quantile estimates used in column 3 were obtained by incorrectly assuming a normal error structure and using an estimated standard error. In this case the root mean squared quantile estimation errors are again lower for the bootstrap estimates in the lower half of the error distribution while they are higher in the upper quantiles. In any case, bootstrapped quantile estimates are fairly accurate and robust to changes in the underlying error structure. In this case it is not clear that the P-S procedure is preferred to the R-B procedure.

Columns 6 through 9 list the quantile estimation results for the one state variable model with gamma errors. The results are similar to the reduced state variable results in Table 1. Again, the R-B quantile estimates have significantly lower root mean squared errors than those of the alternative procedures. The robustness of the quantile estimates indicate that the bootstrap simulation procedure

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[6] The variance of Gamma(6, 91.86)disturbance is $6 * 91.86^2 = 50{,}630$, giving a standard error of 225.

has potential usefulness when the number of state variables must be reduced to facilitate the dynamic programming model.

A Four State Variable - Two Equation Model

The third Monte Carlo study examined bootstrapped disturbance estimates from the following recursive system of equations:

$$R_t = 11.076 + 1.571 R_{t-1} - .6534 R_{t-2} + e_t^R \tag{17}$$

and

$$V_t = -353.76 + 8.0505 R_t + 1.2635 V_{t-1} - .5848 V_{t-2} + e_t^V \tag{18}$$

with $e_t^R \sim$ Normal (0, 10.86) and $e_t^V \sim$ Normal(0, 193.48).[7] In expressions (17) and (18) we assume that e_t^R and e_t^V are independent. The evolution of V_T is thus conditional on current and past rents (R_T and R_{T-1}) and land values (V_T and V_{T-1}). Table 3 presents the results of the Monte Carlo study. Columns 2 through 5 list the quantiles and the quantile estimation results for the full four state variable model. The quantiles of V_{T+1} are conditional on $R_T=R_{T-1}= 135.0$ and $V_T=V_{T-1}=2250$. The forecasts used in column 3 were constructed by assuming independently normally distributed errors and using parameter estimates to predict the quantiles of V_{T+1}. In every quantile (except the 50% quantile), the complete state variable P-S bootstrapped estimates exhibit less bias and (in every case) generates a lower root mean squared estimation error. The R-B bootstrap results are not as favorable but still compare favorably with the results of traditional procedure. In this case, with a complete set of state variables, the P-S bootstrap clearly outperforms the alternative distribution estimation procedures. However, for many applied SDP studies, using four state

[7] The parameters were estimated using a U.S. Department of Agriculture series of cash rents (R_t) and land values (V_t) in North Central Iowa.

variables to predict one variable may make the model impractical due to Bellman's "curse of dimensionality." The deletion of state variables, i.e., information, may be necessary to facilitate the SDP model but comes at the expense of less precise one period ahead distribution estimates.

Columns 6 through 8 of Table 3 present the quantiles and quantile estimation error measures when the state variables, R_{T-1} and V_{T-1}, are deleted. The results indicate that the bootstrap estimates now have some bias. The R-B root mean squared quantile estimation error has more than doubled for most quantiles but are again significantly lower than those of the P-S bootstrap. In neither case is the level of the bias large relative to the true quantile value. The increase in the root mean squared quantile estimation error may be more troubling but appears to be the price paid for discarding a significant amount of information to reduce the number of state variables. Whether the benefit of a computationally feasible SDP model is worth the decreased forecasting precision is a judgement best left to the analyst.

Conclusion

The results of the three Monte Carlo studies indicate that non-parametric bootstrapped estimates of transition probabilities are almost as efficient as parametric estimates when the functional form of the disturbance is known. Additionally, the bootstrapped estimates appear to be robust across differing functional forms. This result is encouraging given the fact that the researcher seldom knows the appropriate functional form for the error distribution. When the researcher is not limited by the number of state variables the P-S bootstrap procedure appears to be slightly preferred to the R-B bootstrap procedure.

When the researcher must discard information to obtain a computationally feasible stochastic dynamic program, the bootstrapping simulation procedures presented above appear to generate acceptable results when exact procedures such as those presented by Burt and Taylor are infeasible due to computational limitations or when symmetry of the time series cannot be exploited. When the set of state variables is reduced, the R-B bootstrap procedure appears to be clearly preferable to the P-S bootstrap procedure in that the R-B procedure almost always generates lower root mean squared estimated quantile errors.

Table 1: Quantile Estimation Errors
Single Equation Model with Normal (0, 225) Disturbances

Quantile	Second Order Process[a]				First Order Process			
		Mean Estimated Quantile Errors				Mean Estimated Quantile Errors		
	Actual Quantile Value[b]	Normal Estimate	P-S Bootstrap Estimate	Residual Bootstrap Estimate	Actual Quantile Value[b]	Normal Estimate	P-S Bootstrap Estimate	Residual Bootstrap Estimate
0.025	1,827	-2[c] (106)[d]	-9 (117)	32 (120)	1,571	-69 (344)	-93 (274)	53 (208)
0.05	1,898	-2 (99)	-15 (102)	24 (106)	1,683	-59 (290)	-86 (242)	37 (179)
0.10	1,980	-3 (91)	-19 (90)	13 (94)	1,812	-46 (229)	-75 (205)	21 (147)
0.1587	2,043	-3 (86)	-21 (81)	5 (88)	1,912	-37 (181)	-66 (174)	10 (121)
0.50	2,265	-5 (77)	-24 (70)	-24 (81)	2,265	-27 (46)	-20 (51)	-21 (55)
0.8413	2,493	-6 (83)	-23 (78)	-50 (96)	2,624	31 (176)	24 (155)	-50 (128)
0.90	2,556	-7 (87)	-23 (85)	-56 (104)	2,724	41 (223)	34 (183)	-60 (155)
0.95	2,638	-7 (94)	-26 (99)	-65 (118)	2,853	53 (285)	48 (222)	-74 (187)
0.975	2,709	-8 (101)	-24 (120)	-73 (136)	2,965	64 (338)	58 (254)	-91 (219)

Notes:

[a] The second order process in $Y_t = 215.89 + 1.679Y_{t-1} - 0.774Y_{t-2} + e_t$. The sample size was 25.

[b] These second order quantiles are conditional on $Y_{t-1} = Y_{t-2} = 2{,}265$. The first order quantiles are conditional on $y_{t-1} = 2.265$.

[c] This value is the mean estimated quantile error.

[d] The values in parentheses are the root mean squared quantile estimation errors.

Table 2: Quantile Estimation Errors
Single Equation Model with Gamma (6, 91.86) Disturbances[a]

	Second Order Process[b]				First Order Process			
		Mean Estimated Quantile Errors				Mean Estimated Quantile Errors		
Quantile	Actual Quantile Value[c]	Normal Estimate	P-S Bootstrap Estimate	Residual Bootstrap Estimate	Actual Quantile Value[c]	Normal Estimate	P-S Bootstrap Estimate	Residual Bootstrap Estimate
0.025	1,919	-87[d] (117)[e]	-34 (74)	2 (66)	1,620	-123 (348)	-124 (273)	26 (186)
0.05	1,957	-55 (90)	-27 (67)	6 (65)	1,710	-89 (287)	-101 (240)	23 (161)
0.10	2,007	-24 (70)	-21 (60)	8 (64)	1,818	-54 (219)	-78 (202)	21 (132)
0.1587	2,050	-5 (64)	-17 (57)	8 (65)	1,908	-34 (169)	-64 (167)	16 (107)
0.50	2,238	28 (79)	-14 (61)	-9 (74)	2,232	35 (56)	3 (47)	6 (50)
0.8413	2,487	0 (102)	-2 (93)	-47 (110)	2,592	67 (195)	61 (174)	-19 (129)
0.90	2,569	-20 (113)	-27 (113)	-60 (130)	2,700	70 (240)	69 (205)	-30 (155)
0.95	2,683	-53 (136)	-36 (144)	-81 (159)	2,862	50 (295)	63 (241)	-65 (195)
0.975	2,789	-90 (163)	-31 (185)	-87 (195)	2,988	48 (347)	69 (275)	-84 (227)

Notes:

[a] The disturbance terms were centered a zero by subtracting $\alpha \cdot \beta = 551.16$ from the generated gamma random variable. The standard error (225) is equal to the normal example in Table 1. The sample size was 25.

[b] The second order process is $Y_t = 215.89 + 1.679Y_{t-1} - 0.774Y_{t-2} + e_t$.

[c] The second order quantiles are conditional on $Y_{t-1} = Y_{t-2} = 2{,}265$. The first order quantiles are conditional on $Y_{t-1} = 2{,}265$.

[d] This value is the mean estimated quantile error.

[e] The values in parentheses are the root mean squared quantile estimation errors.

Table 3: Quantile Estimation Errors
Double Equation Model[a]

Quantile	4 State Variables Included				2 State Variables Included		
	Actual Quantile Value[b]	Mean Estimated Quantile Errors			Actual Quantile Value[c]	Mean Estimated Quantile Errors	
		Normal Estimate	P-S Bootstrap Estimate	Residual Bootstrap Estimate		P-S Bootstrap Estimate	Residual Bootstrap Estimate
0.025	1844	42 (99)[d]	-3 (91)	52 (100)	1581	-57 (264)	85 (229)
0.05	1910	35 (90)	-7 (83)	40 (88)	1682	-46 (235)	73 (205)
0.10	1988	27 (81)	-9 (74)	28 (77)	1803	-36 (200)	58 (184)
0.1587	2047	20 (74)	-11 (70)	20 (71)	1904	-31 (179)	44 (166)
0.50	2260	-2 (63)	-13 (61)	-12 (64)	2258	-5 (138)	1 (128)
0.8413	2472	-24 (73)	-14 (66)	-42 (80)	2621	17 (200)	-49 (163)
0.90	2532	-30 (79)	-12 (72)	-51 (88)	2732	11 (219)	-72 (187)
0.95	2609	-38 (88)	-11 (83)	-63 (101)	2853	28 (259)	-85 (208)
0.975	2676	-46 (97)	-14 (95)	-74 (114)	2965	29 (286)	-103 (232)

Notes:

[a] The two equations are:

$$R_t = 11.076 + 1.571R_{t-1} - 0.6534R_{t-2} + U_t^R \qquad U_t^R \sim \text{Normal}\ (0,\ 10.86)$$

$$V_t = -353.76 + 8.0505R_t + 1.2635V_{t-1} - -0.5848V_{t-2} + U_t^V \qquad U_t^V \sim \text{Normal}\ (0,\ 193.48)$$

[b] These are quantiles of V_t, conditional on $R_{t-1} = R_{t-2} = 135.0$ and $V_{t-1} = V_{t-2} = 2250$.

[c] These are quantiles of V_t, conditional on $R_{t-1} = 135.0$ and $V_{t-1} = 2250$.

[d] The values in parentheses are the root mean squared quantile estimation errors.

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RISK RESPONSES OF LARGE-SCALE CORNBELT FARMERS

by

George F. Patrick, Wesley G. Musser, and Gerald F. Ortmann*

Risk attitudes, perceptions, and responses of producers have intrigued researchers and members of S-232 and its predecessor committees for many years. Young *et al.* dissuaded the W-149 Committee from a national effort to elicit farmers' risk aversion coefficients. However, the S-180 Committee was less fortunate and a 12-state interview effort was undertaken (Patrick *et al.*), albeit on pilot basis, to determine importance of different sources of variability to producers and their ranking and use of various responses to risk. Boggess, Anaman, and Hanson; Wilson, Luginsland, and Armstrong; and Wilson, Dahlgran, and Conklin conducted follow-up studies on more homogenous samples and analyzed socio-economic and business factors related to the ratings of sources of risk and risk responses. This paper reports on a similar study, in which the farmers came to the researchers, analyzing the risk attitudes as well as the sources of risk and managerial responses of large-scale cornbelt farmers from eight states. In addition, some standard psychological methods are utilized in the interpretation and analysis of the data.

The objectives of this paper are to: a) develop some simple, psychology-based, alternative measures of risk attitudes for producers and examine their relationships with observed economic behavior, b) analyze the importance of sources of risk and variability, and c) analyze the importance of managerial responses to risk and factors influencing these responses. The paper is organized in five sections, beginning with a brief description of the procedures and the characteristics of the

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respondents. Second, development of and results for some alternative measures of risk attitudes are presented with an analysis of the relationships with observed economic behavior. In the third section, an exploratory factor analysis of the importance of sources of risk and variability is presented. Next, an exploratory factor analysis of the managerial responses to risk is presented. The factor scores for the managerial responses are used as dependent variables in regressions with socio-economic characteristics and risk attitudes of respondents. The paper closes with some conclusions and implications drawn from these preliminary analyses.

Data and Procedures

Data for this study were collected from participants in the 1991 Top Farmer Crop Workshop at Purdue University. The workshop is a three-day program which provides an update on crop economics and production technology. Participants also have the opportunity to analyze alternative technologies using a linear programming model of their own farm operation. The workshop has been held annually since 1968 and is promoted by direct mailings to about 6,000 farmers in the eastern cornbelt and in the farm press. A fee of $160 was charged for the primary registrant and $60 for additional enrollees, called secondary registrants, per farm. Participants in previous workshops have been involved in prior studies such as Brink and McCarl, and Shapiro, Brorsen, and Doster.

Registrants in the 1991 workshop were mailed a questionnaire and asked to bring the completed questionnaire to the workshop. A total of 82 of the 102 primary registrants returned questionnaires and 80 were usable. Only 18 of approximately 50 secondary registrants completed a special questionnaire dealing with the risk related questions and selected socio-economic information. Near the beginning of the workshop, all individuals, both primary and secondary registrants, were asked to respond to one of two randomly assigned Kogan and Wallach choice dilemmas type of questionnaires. A total of 55 individuals responded to the traditional choice dilemmas questionnaire and 51 other individuals responded to the modified, agriculturally related choice dilemmas questionnaire. All questionnaires were anonymous—respondents were asked for their initials and the last four digits of their social security number to link data for analysis.

Primary respondents were from eight states, with 47.5 percent from Indiana, 26.2 percent from Illinois, and 13.8 percent from Ohio. Other states represented included Iowa, Missouri, Kentucky, Minnesota, and Pennsylvania. The average size of the farm operation was 1,820 acres, and the median farm operated 1,555 acres. About 38 percent of the land operated was owned with share rental being slightly more common than cash rental. The average farm had 850 acres of corn and 652 acres of soybeans. These crops represented an average of 73.6 percent of 1990 gross farm income. Only 23 percent of the farms had 1990 gross sales of less than $250,000 and 35 percent exceeded $500,000. The average age of the primary respondents was 39.7 years and they had completed an average of 14.9 years of school. These participants reflect superior managers compared to most similar studies with the exception of the Wilson, Luginsland, and Armstrong dairy sample that was also used in Wilson, Dahlgran, and Conklin. For further details on the characteristics of the group and the general questionnaire used, see Ortmann *et al.*

The secondary respondents were younger, an average age of 31.4 years, and had completed more years of education, an average of 15.3 years, than the primary respondents. Although 60 percent of the secondary respondents were related to the primary respondent, only 22 percent considered themselves as an equal or co-decision maker. About one-half of the secondary respondents described themselves as having a managerial duty in the farm operation.

Alternative Measures of Risk Attitudes

Musser and Musser argued that the psychological literature suggests that empirical methods to elicit risk preferences and subjective probability distributions based on decision theory are subject to severe limitations. However, psychological measurement scales that have extensive data on their reliability and validity may be useful in these efforts. Likert-type scales such as used by Ajzen and

Fishbein to measure risk preferences and Kogan and Wallach's scale of willingness to assume risk were suggested as psychological measures which might be useful in empirical economic research. While agricultural economists have subsequently devoted less attention to measuring risk preferences, development of satisfactory measurement methods may allow further research.

Likert-type Scales of Willingness to Take Risk

In this study, respondents were asked to indicate their willingness to take risk, relative to other farmers, in four management areas. These were farm production, product marketing, farm finance, and overall farm management. A Likert-type scale ranging from one (much less) to five (much more) was used for each area. Inclusion of the fourth, more aggregate scale reflects the proposition in attitude theory that specific attitudes predict specific behavior while more general attitudes predict general behavior (Fishbein and Ajzen). In the risk measurement area, this proposition implies that the first three scales would be more closely related to risk responses in the traditional areas of farm management and the fourth in overall farm management. Framing the scales in reference to other farmers was designed to give respondents a basis for comparison. It is likely that these scales will not be especially useful in prescriptive studies for individual farmers. However, they may be adequate for behavioral and predictive studies in which the central issue is measurement of differences in risk preferences (Musser and Musser).

The standard psychometric perspective on such scales is that they are interval measures, similar to utility functions in decision theory. Thus, standard parametric statistical procedures are appropriate. Sample statistics for these scales are presented in Table 1. The primary and secondary respondents had similar patterns in their willingness, relative to other farmers, to take risks. Both groups expressed the greatest willingness to take risk in the production area and were the least willing to take risks in the farm finance area. The secondary respondents were more willing than the primary respondents to take risks in the production and overall management areas. However, the differences in means between groups were not statistically significant. All of the willingness to take risks measures, as would be expected, were positively correlated. For the primary respondents, the lowest correlation, 0.376, was between the production and finance areas and the highest, 0.750, was between production and overall farm management. The correlations were all significant at the one percent level. For the secondary respondents, the lowest correlation, 0.366, was between production and overall farm management and the highest, 0.710, was between finance and overall farm management. The correlations for the secondary respondents, except for production and overall farm management, were significant at the five percent level.

A similar question was also included asking respondents to rate their management skills, relative to other farmers, in production, product marketing, farm finance, and overall farm management. A Likert-type scale ranging from one (low) to five (high) was used. Sample statistics are presented in Table 1. The primary respondents rated themselves highest in overall farm management skills and lowest in marketing skills. In contrast, the secondary respondents rated themselves highest in production skills and lowest in marketing skills. With exception of the production area, the secondary respondents rated their skills as significantly lower than the primary respondents.

The willingness to take risks in the marketing area was not significantly correlated (0.166) with the primary respondents' management skills in marketing. However, the correlations between the primary respondents' management skills and willingness to take risk in production (0.326), farm finance (0.393), and overall farm management (0.420) areas were all significant at the one percent level. For the secondary respondents, the correlations between management skills and willingness to take risks were significant at the five percent level only for the marketing (0.652) and finance (0.573) areas. Thus, farmers seem to be more willing to assume risk in areas in which they have greater management skills. Perhaps these greater management skills allow them to reduce risk compared to the farmers with lower management skills in that area.

Choice Dilemmas

Kogan and Wallach developed a scale of the willingness of an individual to assume risk based on choice dilemmas. Individuals are given a questionnaire in which 12 choice dilemmas for real life situations ranging from chess matches to investment, career, and health decisions are described. Each situation concerns a person faced with a choice between two courses of action. One of the courses of action poses a greater risk but is also more rewarding if successful. The respondent is to advise the person in the situation by deciding what probability of success would be sufficient to justify choosing the risky alternative. The six response categories included the individual not undertaking the risky alternative (coded 10) and then ranged from a 9 in 10 to a 1 in 10 chance, by odd numbers, that the risky alternative would be successful. Following Wallach and Kogan (1959), the order of the response categories were reversed for every other choice dilemma.

An overall score is obtained by summing responses over the twelve situations. The potential range of the overall score is 12 to 120. Higher scores indicate greater conservativeness with respect to taking risks (or more risk aversion), while lower scores indicate less conservativeness (or less risk aversion). Wallach and Kogan (1959) found no significant difference in overall scores between men and women. However, there were significant differences on questions which they associated with behavior. Furthermore, older men and women were both significantly more conservative than young (undergraduate) men and women (Wallach and Kogan, 1961).

For this research, 12 agriculturally related choice dilemmas were developed (Appendix A), four of which were nearly identical with the original Kogan-Wallach situations. For example, an individual was described as having developed a severe heart ailment and has the choice of changing many of his strongest life habits or undergoing a delicate medical operation which might succeed or might prove fatal. In the original version, the individual was described as a 45-year old accountant while he was a 45-year old farmer in the agriculturally related choice dilemma. The second paired choice dilemmas involved a manager in a stable employment situation with a large corporation or a large hog operation, with both considering a risky job with a new company involving possible ownership opportunities. The third involved two individuals, one contemplating marriage and the second, formation of a farm partnership. The fourth involved a businessman or a farmer and the possibility of a successful race for a Congressional seat. The other choice dilemmas involved production, marketing, and financial decisions of the type faced by farmers.

Because farming is subject to greater year-to-year variability, and perhaps risk, than many other occupations, it was hypothesized that workshop participants would select more risky alternatives than the general public in the traditional choice dilemmas. Furthermore, it was hypothesized that individuals would be more likely to undertake risky alternatives in situations in which they have had more experience, or perceived skills, as demonstrated by the earlier Likert-type scales. It was hypothesized that individuals responding to the agriculturally related choice dilemmas would be less conservative, have lower scores, than those responding to the traditional questionnaire. This hypothesis is tested for the overall choice dilemmas as well as the paired situations only.

The mean scores and standard deviations by situation and for selected totals are presented in Table 2. The total score on the traditional choice dilemmas of 75.81 for all workshop participants and 76.50 for the primary respondents were virtually identical with the means of 76.56 and 76.32 for 65 and 89 nonundergraduate men and women, respectively, in Wallach and Kogan (1961). Thus, the hypothesis that farmers may be more willing to assume risk than other individuals is not supported by these results.

There were no significant differences between the total scores on the agricultural and traditional choice dilemmas for either all workshop participants or the primary respondent groups. This suggests that farmers are not more willing to assume risk in situations which they know. To limit the analysis to "important decisions," the football and chess game situations, dilemmas 4 and 7, were deleted from the traditional choice dilemmas to obtain SUM1. A value for SUM1 for the agricultural dilemmas was defined as 10/12 of the total agricultural score. SUM1 was significantly lower for the agricultural choice dilemmas, indicating greater willingness to assume risk, for the all participant group. The difference was also in the hypothesized direction for the primary respondent group but was not significant at the 10 percent level.

On the four paired choice dilemmas, it was hypothesized that individuals would be likely to recommend a more risky alternative to another farmer or in an agricultural as opposed to a nonfarm situation. Situations 1, 2, and 12 supported that hypothesis, but only the difference for all participants on situation 2 was statistically significant. Both groups required a higher level of a successful outcome before recommending that another farmer run for Congress, situation 10, perhaps reflecting their views of Congress. The total of the paired choice dilemmas, PAIRED, had no statistically significant differences between questionnaires.

Some additional support for the hypothesis that farmers may be more willing to assume risks in situations they know is provided by choice dilemmas 3 and 5. Agricultural choice dilemma 3 referred to an individual considering an investment of $100,000 in additional hog facilities and the probability of future change in environmental and animal rights policy which would make the facilities worthless. In the traditional choice dilemma, an individual was considering a very profitable foreign investment and the possibility of a change in government resulting in nationalization of the investment. Both the all participant and primary respondent groups were significantly more conservative with respect to changes affecting the foreign investment than the additional hog facilities.

Situation 5 involved an individual in a comfortable economic situation who received a $20,000 inheritance. In the agricultural situation, the choice was between buying an nearby tract of land vs. a tract near the local urban area which might double in value. The traditional choice dilemma was an investment in a "blue chip" stock vs. a stock which might double in value. Again, both the all participants and the primary respondents indicated less willingness to assume risk in the stock situation than for the land investment. In both of these situations, it is likely that farmers were more confident of their subjective probabilities of events in the agricultural context.

The pattern of no differences between the totals of the traditional and agricultural scales but differences between certain related paired choices is related to the general purpose of the Kogan-Wallach scale. The total scores are concerned with predicting general behavior toward risk in a number of situations. These results indicate either scale is appropriate for such a purpose. The similar scores for farmers and nonundergraduates in studies 30 years ago also indicates farmers have similar risk preferences to other individuals. This result suggests that farmers are influenced by the general culture, at least in reference to the general willingness to assume risk. However, the difference on subsets and individual dilemmas concern more specific choices. An agricultural context seems to be important in specific decision situations in which a farmer's experience may be important. General scales can therefore potentially be used to predict general risk behavior in the firm-household context. More specific scales related to the issue at hand may be more useful for specific risk management issues.

<u>Risk Attitudes and Observed Economic Behavior</u>

One of the primary reasons for interest in the risk attitudes of decision makers is to improve understanding and eventually prediction of behavior. Table 3 summarizes the correlations between the willingness to take risk scales and the choice dilemmas scores with age, education, and a number of measures of observed economic behavior. Responses on the four willingness to take risks questions were summed to create the more aggregate scale, RISK. The four individual Likert-type willingness to take risk scales are highly correlated (0.8 or greater) with RISK.

Recall that a high score on the choice dilemmas and a low score on the Likert-type scales are associated with low willingness to assume risk. Therefore, the willingness to assume risks scale should have a negative correlation with the choice dilemmas. The correlations are all negative but quite low. Only overall management and RISK have correlations significant at the five percent level. This significance is as expected since the choice dilemmas are concerned with general behavior toward risk. The low correlations do indicate that the measures are not equivalent. The Likert-type scales could be subject to more measurement error. Like many risk measures used in agricultural economics, single responses are less stable than multiple response items such as the choice dilemma scale (Musser and Musser). Perhaps, multiple Likert-type scales on more specific dimensions of agricultural risk would be more appropriate.

The Likert-type scale of willingness to take risks, relative to other farmers, in production is significantly correlated with education, days to plant corn and soybeans in a normal year, and days to harvest corn and soybeans in a normal year. Given the emphasis of the Top Farmer Crop Workshop on timely planting and harvest operations, this relationship in not unexpected. The marketing scale is significantly related only the days to plant and harvest variables, while the farm finance scale is not significantly related to any of the measures of economic behavior analyzed. Both the overall management and RISK scales are significantly negatively related to the percent of land owned. As the willingness to take risk increases, the percentage of owned land decreases. These results are consistent with the general view that leasing is more risky than ownership of land if financial leverage is held constant.

The total score on the choice dilemmas did have a significant correlation with age, with older individuals having higher scores indicating less of a willingness to assume risk. The total score was also significantly correlated with net worth, debt/asset ratio, and total acres. Wealthier individuals, those with lower debt/asset ratios, and those with smaller farms all tend to be less willing to assume risk. The relationship with wealth is inconsistent with the hypothesis of decreasing absolute risk aversion. However, the relationship of wealth and age may be confounding this relationship.

Overall, the choice dilemmas scale had more significant correlations with these socio-economic variables than the Likert-type scales. However, in contrast to the studies in Young's review, only one of the six measures had a significant correlation with education. The Likert-type scales were more significantly related to the time to plant and harvest variables, which are more specific behavior. The farm finance and aggregate Likert-type scales were not related to the debt-asset ratio while the choice dilemmas were. Thus, the choice dilemmas scale seems more successful in measuring relationships with the respondents' characteristics and behavior. Given that the aggregate Likert-type scales were correlated with the choice dilemmas scale, more research on alternative Likert-type scales may result in better formulations.

Sources of Risk and Variability

Workshop participants were asked to indicate the importance of 15 sources of risk in their farm decision-making on Likert-type scales ranging from one (not important) to five (very important). The sources of risk were similar, but not identical, to those included in the S-180 study (Patrick *et al.*). For example, inflation and world events were excluded as sources of risk, while environmental regulations were introduced. In addition, this questionnaire emphasized the importance of the sources of risk in farm decision-making rather than in crop and livestock production as in Patrick *et al*. This formulation was similar to Wilson, Dahlgran, and Conklin.

The mean importance and relative rankings for the primary and secondary respondents are in Table 4. As might be expected from participants in a crop-oriented workshop, crop price and yield variability were the top rated sources of risk for both groups. The third rated source of risk (injury, illness or death of the operator) was also the same for both groups. Livestock production and price variability was ranked at or near the bottom by both groups and reflects the crop production emphasis of these farms. The primary respondents gave greater importance to government commodity programs and environmental regulations than the secondary respondents. Changes in technology and costs of capital items were rated higher as sources of risk by the secondary than the primary respondent. The range of average ratings, 2.43 to 4.50, was greater for the secondary respondents than the 2.86 to 4.31 range of the primary respondents.

Previous studies of sources of risk have treated these responses as independent. In contrast, attitude research generally considers responses to individual questions as measures of underlying latent variables of sources of risk. For example, changes in the interest rate and credit availability may be alternative measures of risks arising from finance. Factor analysis originated as a method to explore such underlying relationships of attitude responses to latent variables. If such variables do exist, subsequent analysis is greatly simplified compared with the large number of logit models in Boggess, Anaman, and Hanson, and in Wilson, Dahlgran, and Conklin. Therefore, an exploratory factor analysis of the ratings of the importance of 15 sources of risk in farm decision-making was performed for the primary respondents only. Five factors had eigenvalues greater than one and explain 72.5 percent of the variance. A varimax orthogonal rotation was implemented. In general, the sources of risk have loadings which exceed 0.6 on one factor and do not exceed 0.3 on any of the other factors (Table 5). Technology and input prices are the only sources of risk whose loadings exceed 0.3 on more than two factors.

Factor 1 is called the "gross crop income" factor because of the large loadings on both crop yields and crop prices. Other sources of risk with their largest loadings on this variable include the costs of capital equipment and technology. Factor 2, named the "government policy" factor, has both commodity and environmental policy with loadings which exceed 0.7. Land rent and input prices are the only other sources of risk with their largest loadings on factor 2. These two sources also both load quite heavily on the crop production factor. Factor 3 is referred to as the "gross livestock income" factor because of the loadings exceeding 0.9 on both livestock prices and livestock yields. No other sources of risk have loadings which exceed 0.3 on that factor. Factor 4 is called "family" because of the loadings on the illness, injury or death of operator; family relationship changes; and family labor force changes as sources of risk. The final factor is referred to as the "financial" factor because of the high loadings of interest rates and credit availability on this factor. Technology and input prices were the only other sources with loadings greater than 0.3 on the financial factor.

These results suggest that farmers do view risk and uncertainty as having various dimensions but not as many as the individual questions. Prices and yields are not viewed independently. Farmers are concerned with gross income risks rather than production or price risk. Government policies are a separate source of risk rather than being related to price risk. In addition, farmers view family risks as an important source of risk that agricultural economists typically do not consider. Finance is a separate source of risk. Therefore, these factors support the distinction between business and financial risk which is common in agricultural finance. However, the production, marketing, and finance distinctions which are also common in risk-related work in agricultural economics are not supported by these results.

Managerial Responses to Risk

Workshop participants were also asked to indicate the importance of 18 production, marketing, and financial responses to risk. Likert-type scales ranging from one (not important) to five (very important) were used. The responses considered were grouped in the same categories as the S-180 study (Patrick *et al.*), but the individual items were modified considerably.

The mean ratings and the ranking within each area for the primary and secondary respondents are presented in Table 6. In general, the primary and secondary respondents' rankings of the risk management responses in the production category were similar. Having "timely" machinery, being a low-cost producer, and diversification of enterprises were the top three production responses for both groups. The high rating of having timely machinery may be biased as this is a focal point of the workshop's activities. The primary respondents did give considerably more importance to having back-up management/labor than did the secondary respondents which may reflect the primary respondents' greater experience with adverse events.

Forward contracting and participation in the government farm program were the most highly ranked marketing responses to risk by both the primary and secondary respondents. However, the two groups had major differences in the importance and rankings of the other marketing responses. Secondary respondents had a much higher importance for minimum price contracts in which the elevator buys a call for the farmer which allows that farmer to benefit from an increase in the price of the commodity. Secondary respondents also gave substantially greater importance to most marketing responses than the primary respondents. The mean rating of 3.22 given the fifth ranked marketing response, use of commodity options, by secondary respondents actually exceeded the 3.21 rating given the third ranked response, hedging, by the primary respondents. These higher ratings may reflect less experience with these marketing procedures than the primary respondents.

Among the financial responses to risk, both groups ranked liability insurance first. This ranking was followed by debt/leverage management, maintaining financial/credit reserves, and life insurance for partners. None of the other four financial responses were rated more than 3.0 by the primary respondents. Secondary respondents gave the same ranking to off-farm investment as off-farm employment, while primary respondents gave greater importance to off-farm investments than to off-farm employment. Both groups gave greater importance to hail and fire insurance for crops than to multiple peril crop insurance.

An exploratory factor analysis was performed on the primary respondents ratings of management responses to risk. The "life insurance for partners" response was excluded because many of the operations did not involve multiple operators. Preliminary analysis indicated that, despite the high importance given to them, "having timely machinery" and "being a low-cost producer" were associated quite uniquely with factors having eigenvalues of less than one. Thus, these responses to risk were excluded from the following analysis. A varimax orthogonal rotation was used to obtain the factor loadings in Table 7. The five factors explain 61.8 percent of the variance. All but one of the risk responses, government program participation, have factor loadings which exceed 0.5 on one factor. Only off-farm employment has loadings which exceed 0.4 on more than one factor.

The first factor, named the "marketing" factor, has four product marketing related responses with loadings greater than 0.5. The second factor, called a "security" factor, has hail and fire insurance, multiple peril crop insurance and off-farm employment with loadings greater than 0.5. Although the questionnaire classified government program participation as a marketing response, the 0.457 loading on the security factor is much higher than the 0.309 loading on the marketing factor. The third factor is referred to as the "production" factor and has back-up management/labor, diversification of enterprises, and geographic dispersion of production with loadings which exceed 0.5. The fourth factor, called the "off-farm" factor, is unlike the other factors because it is bipolar. Liability insurance has the largest absolute loading, -0.726, with the negative sign indicating it taps a somewhat different dimension than the positively loaded variables. Off-farm employment and off-farm investment have positive loadings which exceed 0.5 on this factor. Government program participation and debt/leverage management are the other variables with negative loadings on the off-farm factor with absolute values exceeding .25. For the fifth factor, the "financial" factor, the financial/credit reserves and debt/leverage management were the responses with the largest loadings.

Unlike the results of the factor analysis of sources of risk, these results provide support for the classification of risk responses into the production, marketing, and financial categories. However, they also suggest two additional dimensions, security and off-farm aspects, of responses to risk. This analysis therefore suggests broader aspects of risk management than often considered in agricultural economics. Government farm programs and liability insurance are viewed separately from marketing and finance categories in which they usually are considered. Perhaps, farmers consider these responses as providing safety-first floors to economic performance while other responses provide an opportunity to trade-off risks and rewards. The off-farm factor also suggests more attention to the diversification of labor, management, and equity between farm and off-farm uses even among large-scale, commercial farm families. These results, combined with the factors on sources of risk, suggest that farm management perhaps needs a broader perspective on risk management.

The factor analysis also suggests that farmers do not view individual questions on responses to risk independently. Various marketing, production, and financial strategies are considered as dimensions of the latent variables of responses to marketing, production, and financial risk. The order and amount of variance explained by each factor, after rotation, is also interesting. Not surprisingly, the marketing factor explained the most variation which is probably related to differences in use of the responses by farmers. Unlike many factor analyses, the second and subsequent factors explain nearly as much variance as the first. The fifth factor being finance may relate to more consensus on these strategies given the experiences of the 1980s.

In an attempt to gain additional understanding of risk attitudes and responses, factor scores were computed for each of the primary respondents and used in a series of regressions with characteristics of the farm operation and the respondent as independent variables. The factor analysis does simplify the reporting and discussion of such analysis compared to the analyses of individual responses in Boggess, Anaman, and Hanson, or Wilson, Dahlgran, and Conklin. The factor scores are normalized variables with a mean of zero and variance of one. They are not the factors, and should be considered only as "error-prone indicators of the underlying factors" (Kim and Mueller). Factor loadings in Table 7 were generally positive, thus a positive regression coefficient indicates that greater importance is given to that variable in the factor.

The regression results are presented in Table 8. The estimated regressions have considerable differences in the overall statistical significance. Similar to Boggess, Anaman, and Hanson and also Wilson, Dahlgran, and Conklin, only a limited number of statistically significant relationships were found. The F values and R^2s of the "traditional" production, marketing, and financial factors are somewhat higher than for the security and off-farm factors. For the off-farm regression, none of the variables were statistically significant at generally accepted levels. Only total acres operated was significant in the security regression. Inclusion of the percent of off-farm investment and net worth did not improve the statistical results. Perhaps this reflects a weakness in our conceptualization of the variables which may be of importance in these nonstandard dimensions of risk attitudes and risk responses.

Age was statistically significant in the production and financial regressions, while education was significant only in the financial regression. The debt/asset ratio was significant in the financial regression, while total acres operated was significant in both the security and financial regressions. The willingness to take risk variables were significant in the marketing, production, and financial regressions. The estimated coefficient of willingness to take risk was negative in the financial regression, but was positive in the other regressions. Farmers may view the responses to risk as increasing, rather than decreasing, risk in areas other than finance. Although this interpretation may be plausible for the marketing area, it does not seem plausible for production. Perhaps multicollinearity and/or specification error is contributing to these signs. Managerial skills were significant in the marketing and financial regressions. The choice dilemmas variable was significant only in the financial regression. The livestock dummy variable was significant only in the production regression, but was substantially larger than its standard error in the marketing regression. The percent off-farm investment was not significant in any of the regressions. Net worth was highly significant in the financial factor regression and significant in the marketing factor regression.

The regression analyses are only preliminary. Results of the factor analysis on risk perceptions should also be included similar to the recent paper of Wilson, Dahlgran, and Conklin. However, several tentative conclusions are apparent. Factor analysis does help to identify underlying patterns in responses—for some of which we have only limited conceptual or empirical analysis. In addition, the analyses are considerably simpler than regression analysis of individual questions. Also, the measures of risk attitudes were significant for the factors on which we have more knowledge. The Likert-type scales performed better than the Kogan-Wallach scale, perhaps because they are more specific. These results indicate the promise of this approach and the need for more research to further refine the scales.

Conclusions and Implications

This study explores the use of simple, psychology-based, alternative measures of risk attitudes. It was found that the willingness to assume risk of participants in the Top Farmer Crop Workshop was virtually identical with previous samples of the general population when faced with similar choices. Evidence was mixed whether workshop participants were more willing to assume risk in an agriculturally related situation. Although the "paired" questions were not significantly different for the groups, individuals did tend to assume more risk in situations with which they were familiar. However, this behavior may be more closely related to their subjective assessment of probabilities rather than a difference in risk attitudes.

The predictive ability of these alternative measures of risk attitudes is encouraging given the complexity of the economic behavior being studied. Use of these measures in future multivariate analysis may be more fruitful. The results also suggest that measurement of risk attitudes should be at the level of the decision which one is trying to predict. Future analyses will include factor analysis of both the traditional and agricultural choice dilemmas to gain greater insight into the risk attitudes of individuals.

The factor analysis of sources of and responses to risk both suggest that more dimensions of risk are involved than are commonly included in our analyses. Clearly, "family" concerns are of importance. "Security" also appears to be an important factor but is largely unrelated to variables which we typically consider of importance in risk situations. Perhaps additional review of psychological literature will provide a better conceptual framework, especially with respect to the management responses to these "nontraditional" sources of risks. Wilson, Dahlgran, and Conklin suggest there may be a one-for-one correspondence between sources of risks and managerial responses. Given the importance of the family and security factors, perhaps disability insurance, pre-nuptial agreements, and buy-sell arrangements may be some of management responses to risk to be included in future research.

The factor analyses also suggest that farmers, at least in the cornbelt, tend to group both sources of and responses to risk differently than agricultural economists. Farmers appear to focus on gross income variability as a factor in both crop and livestock production rather than price and output variability separately. On the responses to risk side, participation in government commodity programs is more of a security response than a marketing response. Finally, it is suggested that future research should not categorize risk responses for respondents as has been common in past questionnaires.

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Table 1. Respondents' Ratings of their Relative Willingness to Take Risk and Managerial Skills by Area of Management.

		Relative Willingness to Take Risk[a]																			
		Production					Marketing					Finance					Overall				
		1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Primary	No.	2	3	25	38	12	2	9	28	32	9	5	19	24	23	9	1	6	27	39	7
	%	2.5	3.8	31.3	47.5	15.0	2.5	11.3	35.0	40.0	11.3	6.3	23.8	30.0	28.8	11.3	1.3	7.5	33.8	48.8	8.8
	Mean			3.67					3.46					3.13					3.54		
	S.D.			(0.87)					(0.93)					(1.11)					(0.81)		
Secondary	No.	1	–	4	8	5	2	3	5	5	3	1	3	8	5	1	1	–	6	8	3
	%	5.6	–	22.2	44.4	27.8	11.1	16.7	27.8	27.8	16.7	5.6	16.7	44.4	27.8	5.6	5.6	–	33.3	44.4	16.7
	Mean			3.89					3.22					3.11					3.67		
	S.D.			(1.02)					(1.26)					(0.96)					(0.97)		
		Relative Management Skills[b]																			
		Production					Marketing					Finance					Overall				
		1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Primary	No.	–	2	21	37	18	1	4	35	28	10	1	7	21	25	24	–	1	17	46	13
	%	–	2.6	26.9	47.4	23.1	1.3	5.1	44.9	35.9	12.8	1.3	9.0	26.9	32.1	30.8	–	1.3	22.1	59.7	16.9
	Mean			3.91					3.54					3.82					3.92		
	S.D.			(0.78)					(0.83)					(1.02)					(0.66)		
Secondary	No.	2	1	3	8	4	2	3	8	4	1	2	3	10	2	1	2	–	9	6	1
	%	11.1	5.6	16.7	44.4	22.2	11.1	16.7	44.4	22.2	5.6	11.1	16.7	55.6	11.1	5.6	11.8	–	50.0	33.3	5.6
	Mean			3.61					2.94					2.83					3.22		
	S.D.			(1.24)					(1.06)					(0.99)					(1.00)		

[a] 1 = much less and 5 = much more relative willingness to take risks.
[b] 1 = low and 5 = high relative management skills.

Table 2. Means and Standard Deviations of Agricultural and Traditional Choice Dilemmas Responses by Question and Selected Totals.[a]

Situation Description	Agricultural		Traditional	
	All[b] (52)	Primary Respondents[b] (31)	All[b] (56)	Primary Respondents[b] (35)
P1. Job change	5.18 (2.00)	5.26 (1.89)	5.56 (2.09)	5.66 (1.98)
P2. Heart surgery	6.38 (1.95	6.93 (1.95)	7.07* (1.96)	7.17 (2.11)
3. Investment and change occurring	6.60 (2.31)	6.97 (2.04)	8.52 (1.66)	8.60 (1.80)
4. Corn harvest/football game	4.77 (2.36)	4.68 (2.48)	4.55 (2.35)	4.25 (2.42)
5. Investments doubling	5.88 (2.39)	6.00 (2.16)	7.20 (2.51)	7.23 (2.55)
6. Marketing/graduate school	6.31 (1.85)	6.77 (1.56)	6.05 (2.25)	6.14 (2.15)
7. Price change/chess match	6.35 (2.53)	7.00 (2.32)	4.30 (2.40)	4.14 (2.07)
8. Buy land/career choice	6.29 (2.50)	6.48 (2.55)	7.24 (2.84)	7.37 (2.83)
9. Irrigation/POW escape	5.83 (2.25)	5.68 (2.44)	5.49 (2.94)	5.71 (3.30)
P10. Congress	7.08 (2.55)	7.35 (2.36)	6.96 (2.72)	6.86 (2.76)
11. New crop/research problem	5.90 (2.35)	6.16 (2.22)	4.84 (2.35)	4.64 (2.29)
P12. Partnership/Marriage	7.25 (2.84)	7.45 (2.67)	7.65 (2.12)	7.81 (2.27)
TOTAL SCORE	73.98 (13.15)	76.71 (13.06)	75.81 (12.13)	76.50 (12.53)
SUM1[c]	61.65 (10.96)	63.92 (10.88)	66.92*** (10.50)	67.91 (10.61)
PAIRED[d] Paired Situations	25.92 (6.19)	26.98 (5.90)	27.26 (5.29)	27.79 (5.21)

[a] *, **, and *** indicate t-tests significant at 10, 5, and 1 percent level, respectively, for difference between agricultural and traditional means.

[b] "All" refers to all workshop participants. "Primary respondents" includes only those individuals who could be identified as primary respondents.

[c] SUM1 excludes responses to situations 4 and 7 for traditional choice dilemmas. SUM1 is 10/12 of total score for agricultural choice dilemmas.

[d] Paired questions, indicated by P, only.

Table 3. Correlations Among Risk Measures, Selected Socio-Economic Characteristics, and Observed Economic Behavior of 66 Primary Respondents.[a]

Variable	Willingness to Take Risk Measures					Choice Dilemmas
	Production	Marketing	Farm Finance	Overall Management	RISK[b]	Total Score
Age	-0.105	0.038	0.072	-0.109	-0.021	0.363***
Education	0.294***	0.093	0.059	0.186	0.173	0.190
Gross sales	0.063	0.096	-0.042	0.042	0.042	-0.147
Net worth	0.020	0.117	0.046	-0.018	0.051	0.285**
Debt/asset ratio	0.177	0.010	0.194	0.118	0.145	-0.267**
Percent off-farm investment	0.132	0.174	0.016	0.027	0.099	-0.050
Total acres	0.166	0.123	0.097	0.059	0.129	-0.239*
Percent owned	-0.175	-0.200	-0.176	-0.349***	-0.256**	0.138
Days to plant crops	0.254**	0.219*	0.138	0.173	0.224*	-0.184
Days to harvest crops	0.251**	0.278**	0.159	0.230*	0.262**	-0.146
Choice dilemma total score	-0.153	-0.201	-0.223*	-0.248**	-0.240**	1.000

[a] *, **, and *** indicate correlations that are significant at the 10, 5, and 1 percent levels, respectively.
[b] Sum of the responses to four individual questions.

Table 4. Relative Importance and Ranking of Various Sources of Risk by Primary (n=80) and Secondary (n=18) Respondents 1991 Top Farmer Crop Workshop.

Sources of Risk	Primary Respondents		Secondary Respondents	
	Mean Rating[a]	Rank	Mean Rating[a]	Rank
Changes in government commodity programs	3.83	4	3.69	6
Changes in government environmental regulations	3.81	5	3.56	7
Crop yield variability	4.21	2	4.19	2
Crop price variability	4.31	1	4.50	1
Livestock production variability	2.86	15	2.43	15
Livestock price variability	3.17	12	2.64	14
Changes in cost of inputs (e.g., feed, seed, fuel, machinery repairs, chemicals, custom services)	3.70	6	3.44	10
Changes in land rents	3.18	11	3.50	8
Changes in costs of capital items (e.g., land, machinery)	3.66	7	3.88	4
Changes in technology	3.54	8	3.88	4
Changes in interest rates	3.48	9	3.50	8
Changes in credit availability	3.05	13	3.33	11
Injury, illness, or death of operator	3.86	3	4.00	3
Changes in family relationships (e.g., divorce, dissolution of partnership)	3.36	10	3.25	12
Changes in family labor force	2.96	14	3.06	13

[a] 1 = not important, 5 = very important.

Table 5. Varimax Rotated Factor Loadings of Sources of Risk for the Primary Respondents in 1991 Top Farmer Workshop (n=75).

Source of Risk	Factor 1 Gross Crop Income	Factor 2 Government Policy	Factor 3 Gross Livestock Income	Factor 4 Family	Factor 5 Financial
Crop yields	0.823	-0.129	0.238	0.219	-0.036
Crop prices	0.799	-0.102	0.299	0.183	-0.061
Costs of capital items	0.684	0.242	-0.075	0.014	0.156
Technology	0.656	0.383	-0.089	-0.042	0.317
Government commodity policy	0.088	0.799	0.053	0.151	-0.036
Government environmental policy	-0.095	0.748	0.195	0.263	0.016
Land rents	0.474	0.596	0.055	0.164	0.155
Input prices	0.394	0.404	0.280	-0.389	0.325
Livestock prices	0.093	0.087	0.958	0.018	0.081
Livestock yields	0.150	0.167	0.913	0.187	0.001
Injury, illness, death of operator	0.192	-0.034	0.173	0.815	0.014
Family relationships	0.015	0.331	0.026	0.710	-0.005
Family labor force	0.147	0.325	0.041	0.666	0.109
Interest rates	0.222	-0.061	0.131	-0.130	0.865
Credit availability	-0.030	0.100	-0.042	0.223	0.857
Percent of variance explained by each factor	18.340	14.753	13.900	13.780	11.747

Table 6. Relative Importance and Ranking of Production, Marketing, and Financial Responses to Risk of Primary (n=80) and Secondary (n=18) Respondents in 1991 Top Farmer Crop Workshop.

Risk Management Responses	Primary Respondent		Secondary Respondent	
	Mean Rating[a]	Ranking	Mean Rating[a]	Ranking
Production Responses				
Diversification of farming enterprises	3.60	3	3.56	3
Geographic dispersion of production	3.11	5	3.17	4
Being a low-cost producer	4.26	2	4.17	2
Having back-up management/labor	3.48	4	3.06	5
Having "timely" machinery	4.31	1	4.28	1
Marketing Responses				
Government farm program participation	3.78	2	3.72	2
Forward contracting the selling price of crops	3.86	1	4.18	1
Hedging the selling price of crops	3.21	3	3.39	4
Minimum price contracts for the selling price of crops	2.49	5	3.50	3
Commodity options to place a floor under the selling price of crops	2.70	4	3.22	5
Financial Responses				
Multiple peril crop insurance	2.18	7	2.88	6
Hail and fire insurance for crops	2.79	5	3.11	5
Liability insurance	4.43	1	4.17	1
Life insurance for partners	3.17	4	3.50	3
Off-farm investments	2.64	6	2.50	7
Off-farm employment	2.13	8	2.50	7
Maintaining financial/credit reserves	3.93	2	3.50	3
Debt/leverage management	3.93	2	3.72	2

[a] 1 = not important, 5 = very important.

Table 7. Varimax Rotated Factor Loadings of Selected Risk Responses for Primary Respondents in the 1991 Top Farmer Crop Workshop (n=75).

Risk Response	Factor 1 Marketing	Factor 2 Security	Factor 3 Production	Factor 4 Off-farm	Factor 5 Financial
Hedging	0.735	0.162	0.058	0.045	-0.093
Minimum price contracts	0.688	-0.072	0.273	0.056	0.193
Commodity options	0.678	0.324	-0.228	-0.014	0.211
Forward contracting	0.535	0.028	0.231	-0.138	-0.041
Hail insurance	0.042	0.834	0.042	-0.161	-0.148
Multiple peril crop insurance	0.330	0.639	0.050	0.221	0.065
Off-farm employment	-0.190	0.564	0.115	0.530	0.162
Govt program participation	0.309	0.457	-0.091	-0.335	0.250
Backup management/labor	-0.243	-0.030	0.813	0.016	0.067
Enterprise diversification	0.214	0.076	0.750	0.039	0.086
Geographic dispersion	0.394	0.050	0.574	0.083	-0.079
Liability insurance	0.112	0.134	0.152	-0.726	0.216
Off-farm investment	0.211	0.079	0.266	0.661	0.114
Financial/credit reserves	-0.004	-0.061	0.002	0.089	0.897
Debt/leverage management	0.115	0.356	0.141	-0.251	0.672
Percent of variance explained by each factor	15.543	13.037	12.515	10.426	10.265

Table 8. Estimated Coefficients and t-Statistics of Variables Associated with Risk Response Factor Scores (n=57).

Variable	Factor 1 Marketing	Factor 2 Security	Factor 3 Production	Factor 4 Off-farm	Factor 5 Financial
Intercept	-3.370 (-2.306)	-0.454 (0.275)	-2.168 (-1.387)	2.209 (1.442)	-1.386 (-1.223)
Age	-0.013 (-0.994)	-0.017 (1.047)	0.030** (2.067)	-0.007 (-0.461)	0.030** (2.428)
Education	0.049 (0.682)	0.082 (0.978)	-0.051 (-0.618)	-0.044 (0.563)	0.109* (1.840)
Debt/asset ratio	0.004 (0.492)	-0.001 (-0.134)	-0.005 (-0.502)	-0.013 (-1.551)	0.016** (2.166)
Total acres operated (100)	0.014 (1.037)	-0.028* (-1.376)	0.019 (1.282)	0.003 (0.214)	-0.030*** (-2.765)
Willingness to take risk[a]	0.266* (1.833)	0.149 (0.307)	0.306* (1.705)	-0.053 (-0.260)	-0.369*** (-3.129)
Managerial skill[b]	0.421** (2.654)	0.083 (0.329)	-0.048 (-0.240)	-0.184 (-0.734)	.333** (2.656)
Choice dilemmas[c]	0.127 (0.996)	0.012 (0.084)	0.054 (0.404)	0.003 (0.021)	-0.282*** (-2.730)
Livestock (dummy)	-0.376 (1.518)	0.006 (0.023)	0.712** (2.614)	-0.064 (-0.248)	
Off-farm investment %	0.007 (1.185)			0.002 (0.428)	
Net worth ($1,000)	-0.496** (-2.658)				.402*** (2.723)
F value	2.862	0.808	1.834	0.576	3.474
R^2	.379	.113	.223	.094	.382

[a] Based on five-point Likert-type scales for "willingness to take risks relative to other farmers" in production, marketing and farm finance for Factors 3, 1, and 5, respectively. The mean of the four scales is used for Factors 2 and 4.

[b] Based on five-point Likert-type scales for "management skills relative to other farmers" in production, marketing and farm finance for Factors 3, 1, and 5, respectively. The mean of the four scales is used for Factors 2 and 4.

[c] Mean response to Kogan-Wallach or agricultural choice dilemmas.

APPENDIX A

AGRICULTURAL CHOICE DILEMMAS

Note: When tabulating responses to this questionnaire, agricultural choice dilemmas 3 and 5 were compared to the original choice dilemma 5 and 3, respectively.

PURDUE UNIVERSITY

DEPARTMENT OF
AGRICULTURAL ECONOMICS

July 21, 1991

Dear Top Farmer Workshop Participant:

What is your risk attitude? How does it compare to other farmers? What effect does it have in your management decisions?

We know that individuals differ in their risk attitudes. We think that these differences in risk attitudes can lead farmers in similar circumstances to make different decisions. We also think that risk attitudes of other individuals involved in a farming operation (spouses, parents, children, partners) may also be important.

The following questions, called Choice Dilemmas, are being developed to help individuals determine their risk attitudes. We are testing different questions and different forms of similar questions in the development of this risk scale.

These choice dilemmas have no right or wrong answers. We are interested in <u>your</u> response. Some of the responses will be discussed in the Tuesday evening program.

To allow us to combine information you have already provided with your responses to the choice dilemmas, please enter your code on the next page.

Sincerely,

George F. Patrick

George F. Patrick
Extension Economist

GFP/kjs

Enclosures

KRANNERT BUILDING • WEST LAFAYETTE, IN 47907

Code: ______________________

(Please use your initials and the last four digits of your social security number.)

Choice Dilemmas Questionnaire

<u>Instructions.</u> On the following pages, you will find a series of situations that are likely to occur in everyday life. The central person in each situation is faced with a choice between two alternative courses of action, which we might call X and Y. Alternative X is more desirable and attractive than alternative Y, but the probability of attaining or achieving X is less than that of achieving Y.

For each situation on the following pages, you will be asked to indicate the minimum odds of success that you would demand before recommending that the more attractive or desirable alternative, X, be chosen.

Read each situation carefully before giving your judgement. Try to place yourself in the position of the central person in each of the situations. There are twelve situations in all. Please do not omit any of them.

1. Carol K, who is single, has been successfully working as the manager of a farrowing unit of a large farm since graduating from college five years ago. She is assured of a lifetime job with a modest, though adequate, salary, and liberal pension benefits upon retirement. On the other hand, it is very unlikely that her salary will increase much before she retires. While attending a pork producers conference, Ms. K is offered a job with a small, newly founded company producing replacement gilts which has a highly uncertain future. The new job would pay more to start and would offer the possibility of a share in the ownership if the company survived the competition of larger existing firms.

Imagine you are advising Ms. K. Listed below are several probabilities or odds of the new company's proving financially sound.

Please check the lowest probability that you would consider acceptable for Ms. K to take the new job.

____ The chances are 1 in 10 that the company will prove financially sound.

____ The chances are 3 in 10 that the company will prove financially sound.

____ The chances are 5 in 10 that the company will prove financially sound.

____ The chances are 7 in 10 that the company will prove financially sound.

____ The chances are 9 in 10 that the company will prove financially sound.

____ Place a check here if you think that Ms. K should <u>not</u> take the new job no matter what the probabilities.

2. Phil B, a 45-year-old farmer, has recently been informed by his physician that he has developed a severe heart ailment. The disease would be sufficiently serious to force Mr. B to change many of his strongest life habits--giving up his farming activities, drastically changing his diet, reducing favorite leisure time activities. The physician suggests a delicate medical operation could be attempted which, if successful, would completely relieve the heart condition. But its success could not be assured, and in fact, the operation might prove fatal.

Imagine you are advising Mr. B. Listed below are several probabilities or odds that the operation will prove successful.

Please check the lowest probability that you would consider acceptable for the operation to be performed.

____ Please place a check here if you think Mr. B should <u>not</u> have the operation no matter what the probabilities.

____ The chances are 9 in 10 the operation will be a success.

____ The chances are 7 in 10 the operation will be a success.

____ The chances are 5 in 10 the operation will be a success.

____ The chances are 3 in 10 the operation will be a success.

____ The chances are 1 in 10 the operation will be a success.

3. Peter T is the owner and operator of a corn, soybean and hog farm. The farm is quite prosperous, and Mr. T has strongly considered the possibilities of business expansion. The choice is between buying additional cropland, which would provide a moderate return on the additional $100,000 investment, or building additional hog facilities. Because of Mr. T's swine management skills, building hog facilities offers a much higher potential return on the $100,000 invested. On the other hand, future environmental and animal rights policies are unclear and may be subject to change. In fact, one proposal would sharply restrict livestock production practices, making the investment in additional hog facilities worthless.

Imagine you are advising Mr. T. Listed below are several probabilities or odds of continued stability in policies with respect to animal rights.

Please check the lowest probability that you would consider acceptable for Mr. T to build additional hog facilities.

____ The chances are 1 in 10 that the livestock production practices will <u>not</u> be sharply restricted.

____ The chances are 3 in 10 that the livestock production practices will <u>not</u> be sharply restricted.

____ The chances are 5 in 10 that the livestock production practices will <u>not</u> be sharply restricted.

____ The chances are 7 in 10 that the livestock production practices will <u>not</u> be sharply restricted.

____ The chances are 9 in 10 that the livestock production practices will <u>not</u> be sharply restricted.

____ Place a check here if you think that Mr. T should <u>not</u> invest in livestock facilities, no matter what the probabilities.

4. Mr. L is in the middle of corn harvesting when his combine has a major breakdown and it begins to rain. Mr. L could purchase a new combine which is currently available from his machinery dealer to be delivered in the morning. On the other hand, Mr. L could arrange for the repair of his combine which would be much less costly than a new combine. The combine would have several years of life remaining after the repairs. However, the machinery dealer does not know when the needed parts will be obtained and repairs can be completed. If Mr. L is unable to resume harvesting after the rain, there will be extra harvesting losses.

Imagine that you are advising Mr. L. Listed below are several probabilities or odds that the repairs will be completed before Mr. L would be able to resume harvesting and avoid extra harvesting losses.

Please check the <u>lowest</u> probability that you would consider acceptable for Mr. L to repair the old combine.

_____ Place a check here if you think Mr. L should <u>not</u> consider repair to the old combine no matter what the probabilities.

_____ The chances are 9 in 10 that the combine will be repaired before harvesting can be resumed.

_____ The chances are 7 in 10 that the combine will be repaired before harvesting can be resumed.

_____ The chances are 5 in 10 that the combine will be repaired before harvesting can be resumed.

_____ The chances are 3 in 10 that the combine will be repaired before harvesting can be resumed.

_____ The chances are 1 in 10 that the combine will be repaired before harvesting can be resumed.

5. Mr. C., a married man with two children, has a farm which provides net income for family living expenditures of $30,000 per year. He can easily afford the necessities of life, but few of the luxuries. Mr. C's father, who recently died, carried a $20,000 life insurance policy. Mr. C would like to use the money as down payment on additional farm land. He is aware of a nearby tract of land which he could easily incorporate into his existing farming operation. He estimates that his net income, after expenses and making the loan payment, would be $1,200 per year. On the other hand, he has also heard about a tract of land near a local urban area. If the city starts growing again, the land could quickly double in value. In the interim, Mr. C believes that he can break-even farming the land. However, if the city continues its current stagnation, the land could decline in value.

Imagine you are advising Mr. C. Listed below are several probabilities or odds that the land will double in value.

Please check the lowest probability that you would consider acceptable for Mr. C to invest in the tract of land near the urban area.

____ The chances are 1 in 10 that the land will double in value.

____ The chances are 3 in 10 that the land will double in value.

____ The chances are 5 in 10 that the land will double in value.

____ The chances are 7 in 10 that the land will double in value.

____ The chances are 9 in 10 that the land will double in value.

____ Place a check here if you think that Mr. C should <u>not</u> invest in the tract of land, no matter what the probabilities.

6. Wes G is a crop farmer who produces 100,000 bushels of corn in a normal year. He has storage for 40,000 bushels and sells the rest at harvest. Currently, he can forward contract 50,000 bushels of corn for harvest delivery at $2.30 per bushel. On the other hand, he can wait to sell his corn at the market price when it is delivered to the elevator. If the market price of corn increases, Mr. G will have a higher income. But there is also some chance the price of corn may decrease and Mr. G would have a lower income. Mr. G must decide whether it would be best to guarantee himself a price on one-half of his expected production now, or wait and sell his grain at harvest.

Imagine you are advising Mr. G. Listed below are several probabilities or odds that waiting to sell at harvest will result in higher income.

Please check the lowest probability that you would consider acceptable for Mr. G to wait to sell at harvest.

____ Please place a check here if you think Mr. G should <u>not</u> wait to sell, no matter what the probabilities.

____ The chances are 9 in 10 that waiting to sell will be a success.

____ The chances are 7 in 10 that waiting to sell will be a success.

____ The chances are 5 in 10 that waiting to sell will be a success.

____ The chances are 3 in 10 that waiting to sell will be a success.

____ The chances are 1 in 10 that waiting to sell will be a success.

7. Jane S is a farmer who uses about 10,000 gallons of diesel fuel annually. Currently petroleum prices are quite high compared with historical levels. A local firm offers to sell Ms. S as much diesel fuel as she would use in the next production season at a price considerably below current levels. At that price, Ms. S would have significant cost savings. However, Ms. S must pay for the diesel fuel now, before its delivery next year. Because petroleum prices are quite volatile, prices may drop substantially before the next production season. This would result in a significant loss for Ms. S.

Imagine you are advising Ms. S. Listed below are several probabilities or odds that diesel prices will not drop below current levels.

Please check the lowest probability that you would consider acceptable for Ms. S to buy the diesel fuel now.

____ The chances are 1 in 10 that diesel fuel prices will not decline.

____ The chances are 3 in 10 that diesel fuel prices will not decline.

____ The chances are 5 in 10 that diesel fuel prices will not decline.

____ The chances are 7 in 10 that diesel fuel prices will not decline.

____ The chances are 9 in 10 that diesel fuel prices will not decline.

____ Please place a check here if you think Ms. S should <u>not</u> buy the diesel fuel, no matter what the probabilities.

8. Mr. P, a 28-year old married farmer, has been shareleasing cropland from several landowners for more than five years. Mrs. W, a widow, is offering Mr. P the opportunity to buy her land at a price slightly below the current market value. Mr. T can obtain the necessary financing, although the land purchase would involve a large debt and put him in a vulnerable financial situation. Purchase of the land would be a good investment, if no major adversity occurs in agriculture. On the other hand, a significant adversity, such as a drought or commodity price decline, could force Mr. P out of farming.

Imagine you are advising Mr. P. Listed below are several probabilities or odds of no significant adversity occurring in agriculture.

Please check the lowest probability that you would consider acceptable for Mr. P to purchase Mrs. W's land.

____ Please place a check here if you think Mr. P should <u>not</u> buy the land, no matter what the probabilities.

____ The chances are 9 in 10 that no significant adversity will occur.

____ The chances are 7 in 10 that no significant adversity will occur.

____ The chances are 5 in 10 that no significant adversity will occur.

____ The chances are 3 in 10 that no significant adversity will occur.

____ The chances are 1 in 10 that no significant adversity will occur.

9. Mr. H has a farm with sandy soils which yield well in years of above average rainfall. Yields tend to be low in normal years and very low if there is a drought. The past couple of years yields have been below average and Mr. H's financial position is not strong. Irrigation is possible in the area. A center pivot irrigation system for 160 acres would require an investment of about $75,000. Mr. H has determined that he would need an increase in his average corn yield of about 35 bushels per acre to pay for the additional seed, fertilizer, water applications and recover his investment in the irrigation system over a ten year period. Experimental irrigation plots have obtained yield increases of 50 to 60 bushels per acre. If Mr. H could obtain this kind of yield increases, the irrigation investment would be very profitable. However, if yield increases of less than 35 bushels per acre were obtained, Mr. H's financial position would worsen rapidly.

Imagine you are advising Mr. H. Listed below are several probabilities or odds that Mr. H will obtain an average corn yield increase of greater than 35 bushels per acre.

Please check the lowest probability that you would consider acceptable to make the investment in irrigation.

____ The chances are 1 in 10 that the yield increase will exceed 35 bushels per acre.

____ The chances are 3 in 10 that the yield increase will exceed 35 bushels per acre.

____ The chances are 5 in 10 that the yield increase will exceed 35 bushels per acre.

____ The chances are 7 in 10 that the yield increase will exceed 35 bushels per acre.

____ The chances are 9 in 10 that the yield increase will exceed 35 bushels per acre.

____ Please place a check here if you think Mr. H should <u>not</u> invest in irrigation no matter what the probabilities.

10. David K is a successful farmer who has participated in a number of civic activities of considerable value to the community. Mr. K has been approached by the leaders of his political party as a possible congressional candidate in the next election. Mr. K's party is a minority party in the district, though the party has won occasional elections in the past. Mr. K would like to hold political office, but to do so would involve a serious financial sacrifice, since the party has insufficient campaign funds. He would also have to endure the attacks of his political opponents in a hot campaign.

Imagine you are advising Mr. K. Listed below are several probabilities or odds of Mr. K's winning the election in his district.

Please check the lowest probability that you would consider acceptable to make it worthwhile for Mr. K to run for political office.

____ Please place a check here if you think Mr. K should not run for political office, no matter what the probabilities.

____ The chances are 9 in 10 that Mr. K would win the election.

____ The chances are 7 in 10 that Mr. K would win the election.

____ The chances are 5 in 10 that Mr. K would win the election.

____ The chances are 3 in 10 that Mr. K would win the election.

____ The chances are 1 in 10 that Mr. K would win the election.

11. Gerald O, a married 30-year old farmer, has obtained a five year lease on 320 acres of farmland. Mr. O currently has sufficient machinery for the land and some operating capital. As he considers a farm plan for the next five years, Mr. O realizes that he might grow vegetables on part of the land. If he could successfully manage vegetable production and markets continued to exist, he would be very successful financially and would probably be able to purchase the land after the five years. If he were unsuccessful in vegetable production and marketing, Mr. O would be likely to lose his existing capital and have to quit farming. On the other hand, Mr O could, as most local farmers are doing, grow corn and soybeans with which he has had experience, but which would be likely to allow only limited financial progress.

Imagine you are advising Mr. O. Listed below are several probabilities or odds that he will be successful in vegetable production.

Please check the lowest probability that you would consider acceptable for Mr. O to go into vegetable production .

____ The chances are 1 in 10 vegetable production would be successful.

____ The chances are 3 in 10 vegetable production would be successful.

____ The chances are 5 in 10 vegetable production would be successful.

____ The chances are 7 in 10 vegetable production would be successful.

____ The chances are 9 in 10 vegetable production would be successful.

____ Please place a check here if you think Mr. O should not attempt vegetable production, no matter what the probabilities.

12. Mr. M, an older farmer, is contemplating forming a partnership with Mr. Z, a man whom he has employed on the farm for more than two years. Recently, however, a number of arguments have occurred between them, suggesting some sharp differences of opinion in the way each views certain matters and how things should be done. Indeed, they decide to seek professional advice from a business counselor as to whether it would be wise for them to form a partnership. On the basis of these meetings with the business counselor, they realize that a well-working partnership, while possible, would not be assured.

Imagine you are advising Mr. M and Mr. Z. Listed below are several probabilities or odds that their partnership would prove to be a well-working one.

Please check the lowest probability that you would consider acceptable for Mr. M and Mr. Z to form a farm partnership.

____ Please place a check here if you think Mr. M and Mr. Z should <u>not</u> form a farm partnership, no matter what the probabilities.

____ The chances are 9 in 10 that the partnership will be a success.

____ The chances are 7 in 10 that the partnership will be a success.

____ The chances are 5 in 10 that the partnership will be a success.

____ The chances are 3 in 10 that the partnership will be a success.

____ The chances are 1 in 10 that the partnership will be a success.

The Stochastic Agricultural Sector Model: Applications to Global Climate Change and Farm Program Revision

By

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March 25 1993

* The first listed author is a Professor in the Department of Agricultural Economics, Texas A&M University, the third is an Associate Professor at the University of Nevada, Reno, the fourth is an Associate Professor at the University of Missouri, and the second and fifth authors listed are research associates at Texas A&M University. This research arose from efforts under USDA CSRS Regional Project S-232 entitled "Quantifying Long Run Agricultural Risks and Evaluating Farmer Responses to Risk". We are indebted to cooperating researchers in S-232 who provided us with much of the data used to simulate yield variability, with special thanks to Vern Eidman and Mustapha Hammida for providing livestock data. Karen Thaysen's work in representing crop yield variability is also especially appreciated.

The Stochastic Agricultural Sector Model: Applications to Global Climate Change and Farm Program Revision

The purpose of this paper is to refine and expand upon an earlier presentation of the agricultural sector model (ASM) developed as a part of Southern Regional Project S-232. The conceptual origins of the model owe much to the sectoral models developed by Hazell and Scandizzo (1974, 1977) and Hazell and Pomareda (1981). However, all of the Hazell and associates' models preclude behavior influenced by anything other than the average market price or revenue variability. Thus, for example, export levels are based on averages and do not vary given bumper crops or droughts. This paper extends the HS and HP models to include: (1) consideration of producer behavior predicated upon response to an empirical distribution of discrete yield and, consequently, price events; (2) situations where segments of the sector can alter enterprise levels in response to realized yield and price outcomes, while other segments plan according to revenue expectations; and (3) yield risk for commodities which may not be entirely sold via explicit demand curves but rather may be sold in part or whole as intermediate goods. The formulation assumes that producers make acreage decisions before actual prices and yields are known, although yield distributions and demand curves are known. Subsequently, a realized distribution of discrete output and prices will result. Processing and other marketing decisions are made conditional on total output of the primary commodities by state of nature.

The Hazell-Scandizzo Model

The assumptions of the HS sectoral model regarding uncertain yields are: (1) yields are the sole source of risk (endogenous prices will be random due to random total production); (2) producers operate in a competitive environment, form revenue expectations and maximize EV utility; and 3) producers make decisions before prices and yields are known. HS formalize the linear demand model as:

[1] $\quad \text{Max}_X \; CPS = E[X'N(A - 0.5\,BNX)] - C'X$

subject to

$$DX \leq b$$

$$X \geq 0$$

where $E[\cdot]$ is the expectation operator, X is a vector of production levels, N is a diagonal matrix of actual yield outcomes under state s, A-B(NX) is a set of quantity dependent demand equations, C is a vector of unit activity costs, D is a matrix of resource usage coefficients, and b is a vector of resource endowments.

For solution purposes, HS (1975, 1977) and HP manipulate the expectations operator in [1] to obtain:

$$[2] \qquad X'E(N)A - 0.5\, X'\, E[NBN]\, X \; - \; C'X$$

$$= \; X'E(N)\,(A - 0.5BE[N]X) - 0.5X'V(NBN)X - C'X$$

where V(NBN) is the covariance matrix of weighted yields. Risk averse behavior can be included in the model by adding $-\phi(X'\Omega X)^{1/2}$ to the objective function, where Ω is the variance-covariance matrix of per acre net revenues and ϕ is an appropriately aggregated measure of producer risk aversion. Lacking practical aggregation procedures, the incorporation of the $-\phi(X'\Omega X)^{1/2}$ term assumes all farms in the model face identical revenue variance and covariance conditions while having identical aversion to risk (Hazell and Norton).

Including Adaptive Behavior and Derived Demands

Incorporation of adaptive behavior and implicit demands of the processing sector into the HS model may be accomplished by using two stage or discrete stochastic programming with recourse (SPR), as developed by Dantzig, generalized by Cocks, and used in Lambert and McCarl (1985, 1989), and McCarl and Parandvash.[1] The SPR formulation of the problem includes market clearing rows for each state of nature with objective function expectations explicitly calculated by considering the revenue outcomes under each discrete state of nature. Further, processing activities are included that are dependent upon the yield outcomes under each state. The resultant model is:

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1 See Boisvert and McCarl for a recent review.

$$[3] \quad \text{Max}_Q \ \text{CPS} = \sum_s \left\{ \theta_S [Q_S'(A - 0.5\,BQ_S) - G'Y_S] \right\} - C'X$$

subject to

$$\begin{array}{lll} Q_S + HY_S - N_SX & \le 0 & \text{for all s} \\ MY_S & \le e & \text{for all s} \\ DX & \le b & \\ Q_S, Y_S, X, & \ge 0 & \end{array}$$

where the variables are Q_S, a vector of final goods resulting either directly from farm production (N_SX), or from processing activities, (HY_S), under state of nature s; Y_S, a vector of state of nature dependent processing levels which, when applicable, convert some or all of primary production, N_SX, to final goods. X is a vector of production levels chosen prior to knowledge of state of nature. The parameters for the model are: θ_S, the probability of state of nature s occurring; A and B, the demand curve parameters; G, a vector of per unit processing costs; H, a matrix of product usage and final good supply by the processing activities;[2] M, a matrix of resource usage by the processing activities; N_S a matrix of yields under state of nature s; D, a matrix giving resource usage by X; and e and b, the resource endowments.

There are four differences between the stochastic model [3] and the HS/HP formulations:

1. Explicit outcomes under each state of nature are determined rather than the expected value and variance parameters resulting from the HS/HP models. For example, a vector of prices for a particular final good is derived. These vectors of discrete outcomes may prove more robust to the decision maker who, for example, wishes to apply a Savage criterion in policy selection.

2. In [3], a portion of the primary production output may be diverted from final demand to the processing sector. Q_S accumulates the quantity of output that is

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2 All elements in a row of H will equal zero when farm production of a certain product faces final demand rather than being used as an input into further processing.

directly sold in the final market. HY_S accumulates the quantity of N_SX used in processing as an intermediate input, as well as the supply of processed goods sold to final demand.

3. Some commodities may not have final demand and may only be used in the manufacture of processed goods (for example, the demand for soybean meal is derived from market conditions facing livestock feeders). In these instances, all of output N_SX may be exhausted through processing levels Y_S and input requirements for N_SX represented in matrix H. The HS/HP family of models could not directly handle riskiness in such cases since the explicit demand curve parameters they require to form their objective function [2] are not present. The optimality conditions reported by HS/HP to determine expected prices fail because of the absence of explicit demand function parameters essential to their calculations.

4. Processing (Y_S) and consumption (Q_S) are state of nature dependent, but production (X) is not. Thus, processing and consumption (including trade) are adaptive, whereas primary production decisions are based on an expected distribution of yield outcomes.

Optimality conditions for the SPR sectoral model are detailed in Lambert et al. In short, these conditions ensure that:

1. Shadow prices on primary product balance rows equate producers' expected unit revenues from the production of a primary commodity with the direct variable production cost plus the resource costs.

2. Processing activities are chosen such that the marginal revenue from processing activities must be less than or equal to marginal costs under each state of nature. Marginal costs consist of direct costs, the opportunity costs of resources used in processing, and the value of the intermediate goods purchased from the primary sector and used in processing.

3. Finally, explicit market clearing prices result from the product balance rows of goods sold to final demand. This is similar to the standard sector model, with the addition that goods that are state dependent return prices under each state.

Two Empirical Applications

An existing empirical U.S. agricultural sector model (ASM) was modified to incorporate yield outcomes and adaptive processing activities that are dependent upon state of nature. The resulting stochastic programming with recourse agricultural sector model , or SPRASM, has evolved from a model originally developed by Baumes, and is described more fully in Chang et al. and He. The SPRASM is a price endogenous mathematical programming model, employing constant elasticity functions for domestic and export demand and for various price sensitive factor supplies. Production and factor usage are specified for the ten USDA crop reporting regions. Processing activities are currently defined at the national level.

An additional modification in SPRASM requires commodity inventories to be explicitly modeled. This prevents activities such as cattle feeding that are dependent on state of nature sensitive production activities from being constrained by the worst yield scenario considered in the model. Consequently, state of nature dependent inventory variables are added to the commodity balance rows. An additional equation is added for each commodity that equates expected stock additions and withdrawals. A cost of 4% of the commodity price is added for states of nature in which net stock additions are positive.

State of nature dependent yield outcomes were developed for selected crop and livestock activities.[3] Time series procedures were used to fit historical yield and harvested acreage series for the 1977 to 1989 period and to forecast 1990 yields.[4] Residuals from these regressions were considered to measure yield variability resulting from unpredictable weather or other environmental factors. Thus, 13 equally likely states of nature were generated by adding the thirteen residuals to the 1990 forecasted yields. The simulated yields across regions were identified by year, thus preserving both interregional and intercrop correlations among the yields.

[3] Crops with state of nature dependent yields are cotton, corn, soybeans, wheat, sorghum, rice, barley, oats, hay, silage, sugar beets, and sugarcane. Stochastic animal product yields were included for beef feeding, feedlot operations, pig finishing, beef stockers, and poultry.

[4] Procedures are discussed in further detail in Thaysen. Historical livestock production data were collected by subcommittee 1 of S-232.

Agricultural Impacts of Global Warming

He has recently used the SPRASM model to determine the welfare effects resulting under two alternative scenarios for future global climate change resulting from industrialization. Base runs for the SPRASM model resulted from calibration of the model to reproduce 1986 price and production conditions. Two commonly used global weather models, the NASA/Goddard Institute of Space Studies (GISS) model and the Princeton Geophysical Fluid Dynamics Laboratory (GFPL) model, were used to represent regional impacts of temperature and precipitation changes resulting from increasing atmospheric carbon dioxide concentrations (see Adams et al. for evaporation, precipitation, and temperature implications of these two models). EPIC (Erosion/Productivity Impact Calculator) was used to simulate the mean and variability of crop yields and mean irrigation water use under the alternative climate projections. Simulations were limited to climatic change impacts on five crops: cotton, corn, soybeans, wheat, and sorghum. Although 1986 farm program provisions were used in the calibration runs, all program provisions were deleted from the runs used to depict future effects of climate change. Given the long term analysis and the uncertain future of any or all farm program provisions, ignoring the program was considered to provide the most conservative estimates of climate change impacts.

He found mixed results in the EPIC simulations. Yield changes were sensitive to the crop considered, geographic location, and whether the crop was irrigated. Most mean yields increased, except in some southern regions. Yield variations also were dependent on crop and region, though cotton and soybean yields exhibited higher standard deviations in most regions.

Table 1 presents price and production solutions under the base conditions, as well as the two climate change models. In general, crop production is expected to increase under both of the climate change models, with ambiguous impacts on average prices. Price differences among the three models result not just from the quantity of output sold to final demand, but also from shifts in regional patterns of production. Resource values and substitution possibilities determine the total costs of production and, under alternative regional production patterns, these costs will differ. The variances of most crop prices and productions levels also decline, with the exception of cotton, barley, and sugar beets. Differences in responses between the two models indicate that prognoses of agricultural impacts of future climate change are sensitive to the climate models used. It is worth noting that, since crop-induced yield variability is the only source of risk in this version of the model, livestock solutions are deterministic and are not significantly affected by climate change.

The distributions of welfare changes resulting from climate change are presented in Table 2. The results indicate similar mean and variance changes under both climate models. Domestic consumers surplus increases slightly on average, with large decreases in the variability of surplus under the different states of nature. One aspect of the solutions results from the wide-spread droughts occurring in 1980, 1983, and 1988. In the base runs, production was lower and prices were higher in these years. The decreases in consumers surplus were, however, lower in these years under both climate models. This may indicate increased reliance on irrigation following climate change which consequently improves farmers' abilities to adjust to drought conditions.

Average increases of 8% and 5%, respectively, are predicted in producers surplus under the GISS and the GFDL scenarios, with 20% decrease in variation. However, producers surplus was below the base level for three of the states of nature, indicating that the direction of change in producers surplus remains uncertain without knowledge of which state of nature will actually occur.

On average, the welfare changes from climate warming are expected to be favorable to both individual subsectors and society as a whole (at least in terms of impacts on agricultural markets). However, while the standard deviation of the individual sectors' welfare decreases, the standard deviation of overall welfare increases under both climate warming scenarios. This suggest a substantial increase in the covariance of the individual surplus measures as a result of climate change. Without the DSP formulation, the effects of climate change on the interaction among the individual sectors cannot be expressed.

A natural question arising from the consideration of state of nature dependent outcomes is whether the value of the solution is greatly improved by incurring the much greater data and computational costs associated with the stochastic model. He addressed this question by solving the model under the 1977 HS formulation, where expected yield values over all states of nature are used instead of the discrete outcomes. Table 3 shows the percentage changes in prices and production from the 1986 base. Prices of most crops fall because of predicted increases in production levels. In contrast to the stochastic model, livestock prices also decrease due to the increases in their production levels.

Surplus measures also increase in the deterministic model (table 4). The increases are largely due to the higher commodity supplies and lower market prices. Thus, domestic consumers and producers both benefit. In percentage terms, the 1% increase in consumers surplus is about double the average expected in SPRASM. Producers' surplus is also about double that of the expected values under the stochastic model. One may also compare the distributional implications of using stochastic yields in the climate change assessment. Differences between the mean of the stochastic model and the deterministic welfare measures were larger under both climate scenarios. This would seem to indicate an increase in the uncertain (or stochastic) component of total welfare as a result of climate change. This highlights the importance of considering the entire yield distribution instead of using mean values in the assessment of future climate changes. A formal t-test of this result in He concluded that there is a significant difference in the total social welfare measure of climate change between the deterministic and the stochastic models.

Farm Program Modifications

Chang et al. have recently used the deterministic ASM to determine the effects of farm policy changes on agricultural production, prices, input usage, trade, and the welfare distribution of various policy scenarios. Chang et al. incorporated four major provisions of the 1985 Farm Program: (1) the target price and associated diversion payments; (2) the commodity price support loan; (3) the marketing loan for rice and cotton and generic PIK certificates; and (4) 0/92, 50/92, and paid diversion acreage. Using expected crop and livestock yield values, the authors calculated the expected levels and the distribution of welfare effects between domestic and foreign interests from decreasing target prices and loan rates from their 1986 levels.

A similar analysis of the impacts of changes in farm program target prices and loan rates was conducted by incorporating state of nature dependent outcomes using SPRASM. The farm program analyses were based on a more recent version of the model than He's, in which several livestock activities were also modeled under stochastic yield assumptions. Thus, not only is the production of fed beef, for example, dependent upon the state of nature feedgrain outcomes, but beef produced per cow in the breeding inventory also reflects the year to year variability observed over the 1977-1989 period.

Changes in the farm program were simulated by incorporating reductions in target prices and loan rates in 5 percent increments up to 25 percent, then removing program supports entirely. Slight reductions occur in both consumers and foreign surplus as a result of the farm support reductions generally due to reduced consumption resulting from higher commodity prices. Producer surplus is also reduced due to rent reduction resulting from lower returns to land and farm labor. The decrease in producers' surplus is consistent with past analyses of the welfare impacts of agricultural price supports (Chang et al.). Using SPRASM, one sees not only a decrease in producers surplus as market and farmer prices converge, but also a decrease in the standard deviation of this surplus. One cause of this drop is the fall in the high producers' surplus values observed in the base model under some states of nature. For example, the maximum of $29.1 billion in PS under the base can be compared with the no FP maximum of $20.5 billion (-29.6%). Respective minimums fall from $21.8 to $17.1 billion (-21.5%).

Market prices for program crops increase for corn, wheat, sorghum, rice, and barley. Price decreases occur for cotton and soybeans. An insignificant fall in oats prices also occurs. As with He's results, these price changes cannot be directly attributed to changing production levels, as shifts in regional patterns of production change the value of resources used in the production of the commodities. Prices of other primary and secondary products are also affected by the changes in the farm program. For example, poultry prices increase, largely due to increases in the price of feedgrains and the limited substitution possibilities for feedgrains in poultry production. Beef prices are not as sensitive as poultry prices since a larger share of the procuction costs for beef are due to roughage inputs.

Concluding Comments

A number of sector models including risk have been developed following Hazell and Scandizzo and Hazell and Pomareda. These models have, however, depended upon the existence of explicit demand curves for all goods, nonadaptive decision making even in cases where intermediate product supplies are known when processing decisions are made, and a producer objective function in which only the first two moments of net revenue are used.

The model discussed here is a modified partial equilibrium model which incorporates discrete stochastic events in the manner of stochastic programming under recourse. This modified model has at least two advantages. First, estimates are generated of price, yield, revenue, processing and consumption levels under each discrete state of nature. Variances of these variables and activities, as well as of the resulting social welfare measures, are easily derived. In addition, the covariance structure among the variables is maintained by use of historical inter-regional and inter-year relationships of the stochastic parameters. Second, the model portrays state of nature dependent, adaptive decision making in the marketing channel. Primary producers respond to a distribution of possible yield and resultant price outcomes. Processors then adapt their use of the intermediate farm output to observed farm production under each state of nature.

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Table 1. **The Impact of Climate Warming on the Means and Standard Deviations of Commodity Prices and Production from Stochastic Runs**

Commodity	BASE Mean	BASE Std	GISS Mean	GISS Std	GFDL Mean	GFDL Std
I. Prices						
Cotton	472.67	16.20	476.87	15.83	469.82	16.06
Corn	1.95	0.10	2.18	0.10	2.07	0.09
Soybeans	5.94	0.80	4.78	0	4.78	0
Wheat	3.18	0.13	3.24	0.14	3.09	0.14
Sorghum	1.92	0.09	2.12	0.09	1.99	0.09
Rice	14.66	0.75	12.70	0.81	14.77	0.81
Barley	1.32	0.13	1.67	0.12	1.60	0.12
Oats	2.25	0.08	2.42	0.08	2.29	0.08
Silage	21.22	14.81	14.04	6.15	15.81	7.82
Hay	57.14	18.22	39.75	6.61	47.01	8.38
Sugarcane	195.41	11.48	176.11	10.21	190.46	10.81
Sugar beets	195.41	11.48	176.11	10.21	190.46	10.81
Nonfed Beef	36.81		36.82		37.09	
Fed Beef	54.86		54.79		55.14	
Poultry	233.00		233.74		230.91	
II. Production						
Cotton	7.99	0.54	8.136	0.63	8.12	0.64
Corn	5.69	0.644	5.73	0.52	5.60	0.49
Soybeans	1863.39	217.43	2259.17	154.30	2125.29	168.43
Wheat	1916.53	112.33	1960.74	131.49	1980.66	111.02
Sorghum	537.15	54.23	487.02	43.93	555.34	55.74
Rice	107.58	3.17	107.52	3.67	105.05	3.01
Barley	540.72	44.26	546.26	50.30	554.37	44.90
Oats	430.18	34.58	485.51	35.12	456.02	34.50
Silage	103.63	4.62	131.24	3.97	123.03	4.15
Hay	181.25	6.88	171.93	4.59	159.12	4.46
Sugarcane	2.41	0.19	2.79	0.12	2.18	0.16
Sugar beets	8.97	0.33	14.25	0.53	13.47	0.50
Nonfed Beef	132.83		132.83		132.41	
Fed Beef	282.66		282.81		282.08	
Poultry	32.76		32.73		32.88	

Note: Mean gives the average result.
Std gives the standard deviation of the result

Table 2. Impact of Global Climate Change on the Means and Standard Deviation of Welfare Distribution of U.S. Agriculture Economies from Stochastic Runs (in 1986 dollars)

	Climate Scenarios						Percentage Change			
	BASE		GISS		GFDL		GISS		GFDL	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Domestic C.S.	794.13	1.39	798.22	0.72	797.09	0.81	0.51	-47.97	0.37	-41.69
Domestic P.S.	14.01	0.87	15.13	0.62	14.66	0.69	7.79	-28.94	4.62	-20.58
Total Foreign Surplus	62.46	0.80	63.04	0.23	63.32	0.24	0.94	-71.10	1.38	-70.17
Total Social Surplus	870.60	1.15	876.39	1.21	875.07	1.33	0.67	4.76	0.51	15.26

Note: Mean gives the average result.
Std gives the standard deviation of the result.
C.S. stands for consumers' surplus.
P.S. stands for producers' surplus.

Table 3. Percentage Changes of Commodity Prices and Production Levels from Climate Change in Deterministic Runs

	Prices		Production	
Commodity	GISS	GFDL	GISS	GFDL
Cotton	-0.16	-0.08	0.11	0
Corn	-4.12	-6.47	10.89	14.29
Soybeans	-6.10	-6.10	84.78	82.91
Wheat	3.97	-2.65	-1.72	-0.43
Sorghum	4.91	-3.68	-4.98	-4.27
Rice	-20.97	-11.00	6.18	3.00
Barley	-18.88	-8.39	2.92	-2.91
Oats	11.68	0.73	14.47	22.69
Silage	-38.79	-31.31	29.29	26.15
Hay	-50.90	-35.62	27.93	23.45
Sugarcane	-73.32	-75.44	400.54	408.70
Sugar beet	-73.32	-75.44	-31.98	-27.48
Nonfed Beef	-10.86	-7.64	4.77	3.31
Fed Beef	-11.92	-8.76	5.05	3.66
Poultry	-0.31	-1.89	1.23	0.76

Table 4. Aggregate Economic Effects of Global Climate Change on U.S. Economic Welfare from BASE, GISS, and GFDL deterministic Runs (in 1986 dollars)

		Climate Scenarios		Percentage Change	
Economic Surplus	BASE	GISS	GFDL	GISS	GFDL
		(billion dollars)		(percent)	
Domestic C.S.	791.03	800.43	799.02	1.19	1.01
Domestic P.S.	15.86	18.39	18.56	15.95	17.02
Total Foreign Surplus	64.16	63.64	63.78	-0.81	-0.59
Total Social Surplus	871.05	882.46	883.77	1.31	1.46

Table 5. Means and Standard Deviations (in parentheses) of Welfare Distributional Effects under Alternative Farm Program Support Levels (1986 values in millions of dollars and percentage changes from 1986 FP for reduced FP supports).

		Percentage Reduction		
	1986 FP	-10 %	-20 %	No FP
Consumers Surplus	804,497 (1,354)	-0.20% (0.77)	-0.23% (6.76)	-0.23% (19.32)
Producers Surplus	25,984 (1,945)	-11.95% (-65.01)	-18.61% (-50.56)	-28.62% (-40.57)
Foreign Surplus	66,287 (408)	-1.00% (3.81)	-1.62% (3.93)	-2.13% (13.62)
Total Surplus	896,768 (3,148)	-0.60% (-43.18)	-0.87% (-56.30)	-1.20% (-65.26)
Government Payments	13,580 (1,453)	-30.33% (-46.14)	-47.77% (-57.83)	-100% (-100)
Net Social Benefit	883,188 (1,790)	-0.14% (-30.35)	-0.15% (-44.69)	0.32% (-38.91)

Table 6. Selected Primary and Secondary Commodity Market Prices (with standard deviations in parentheses) under Alternative Farm Program Support Levels

	1986 FP	Percentage Reduction -10 %	Percentage Reduction -20 %	No FP
Primary Commodities				
Hay	$59.51	$57.95	$56.32	$52.53
	(5.27)	(5.71)	(6.97)	(6.41)
Sugar Beets/Cane	$396.88	$393.00	$383.14	$362.47
	(12.00)	(12.11)	(12.10)	(11.99)
Slaughter Hogs	$43.59	43.96	44.03	44.17
	(4.91)	(3.47)	(3.25)	(2.07)
Beef Slaughter	$53.71	54.48	54.56	54.71
	(0.66)	(1.04)	(1.19)	(1.48)
Poultry	$215.32	227.95	234.07	240.75
	(7.62)	(9.18)	(9.01)	(9.03)
Secondary Products				
Feedgrains	$17.49	22.93	24.67	28.24
	(1.26)	(1.66)	(1.64)	(1.76)
Soybean meal	$9.71	9.01	8.98	8.32
	(0.39)	(0.52)	(0.49)	(0.50)
Fed Beef	$207.05	208.34	208.48	208.74
	(1.11)	(1.76)	(2.02)	(2.49)
Pork	$152.84	153.35	153.44	153.65
	(6.90)	(4.88)	(4.57)	(2.91)
Fluid Milk	$19.78	19.81	19.79	19.75
	(0.10)	(0.11)	(0.10)	(0.08)
Canned Goods	$817.46	$819.13	$818.39	$817.21
	(1.68)	(1.63)	(1.67)	(1.64)
Ethanol	$993.38	1133.36	1172.23	1275.83
	(20.73)	(22.23)	(24.06)	(23.07)

Table 7. **Farmer and Market Prices (with standard deviations in parentheses) for Commodity Crops under Alternative Farm Program Support Levels.**

		Percentage Reduction		
	1986 FP	-10 %	-20 %	No FP
Cotton - Farmer price	$500.48	525.38	509.97	401.97
	(15.98)	(16.56)	(16.58)	(16.73)
Market price	$420.55	417.27	413.69	401.97
	(16.91)	(16.88)	(16.84)	(16.73)
Corn - Farmer price	$2.70	2.86	2.89	2.37
	(0.02)	(0.13)	(0.13)	(0.09)
Market price	$1.67	2.01	2.13	2.37
	(0.08)	(0.09)	(0.09)	(0.09)
Soybean - Farmer price	$6.54	6.20	6.09	5.70
	(0.32)	(0.31)	(0.31)	(0.33)
Market price	$6.54	6.20	6.09	5.70
	(0.32)	(0.31)	(0.31)	(0.33)
Wheat - Farmer price	$4.11	3.68	3.28	3.10
	(0.02)	(0.04)	(0.10)	(0.14)
Market price	$2.46	2.84	3.14	3.10
	(0.10)	(0.13)	(0.14)	(0.14)
Sorghum - Farmer price	$2.37	2.56	2.57	2.12
	(0.03)	(0.10)	(0.10)	(0.09)
Market price	$1.51	1.82	1.93	2.12
	(0.08)	(0.09)	(0.08)	(0.09)
Rice - Farmer price	$13.60	13.66	13.05	13.63
	(0.51)	(0.52)	(0.50)	(0.68)
Market price	$9.79	10.22	9.99	13.63
	(0.50)	(0.52)	(0.50)	(0.68)
Barley - Farmer price	$2.19	2.09	1.90	2.05
	(0.04)	(0.07)	(0.08)	(0.15)
Market price	$1.80	1.85	1.72	2.05
	(0.08)	(0.13)	(0.15)	(0.15)
Oats - Farmer price	$2.10	2.16	2.17	2.08
	(0.08)	(0.18)	(0.18)	(0.20)
Market price	$2.10	2.16	2.17	2.08
	(0.08)	(0.18)	(0.19)	(0.20)

Table 8. Mean and Standard Deviation (in parentheses) Production Levels of Commodity Crops under Alternative Farm Program Support Levels.

		Percentage Reduction		
	1986 FP	-10 %	-20 %	No FP
Cotton	7323	7367	7396	13,748
(Bales)	(549)	(555)	(564)	(1055)
Corn	7381	6671	6764	11,295
(1000 Bu)	(640)	(573)	(575)	(964)
Soybeans	1677	1704	1722	1765
(1000 Bu)	(127)	(131)	(133)	(137)
Wheat	2377	2217	2041	2177
(1000 Bu)	(141)	(138)	(131)	(136)
Sorghum	900	837	780	1242
(1000 Bu)	(84)	(82)	(77)	(122)
Rice	101	100	100	164
(1000 cwt)	(3)	(3)	(3)	(5)
Barley	643	670	639	927
(1000 Bu)	(53)	(55)	(52)	(78)
Oats	483	481	540	527
(1000 Bu)	(37)	(36)	(42)	(40)

The Stochastic Agricultural Sector Model: Applications to Global Climate Change and Farm Program Revision

Discussion

Wayne I. Park[1]

The stochastic agricultural sector model developed by McCarl *et al.* seems ideally suited to assess the aggregate impacts of global environmental change on the U.S. agricultural sector. Adams *et al.* examined the economic implications for the agricultural sector of changes in average crop yields due to climatic changes. Their analysis suggested that differences in the regional impacts would likely induce regional adjustments in crop production. However, changes in levels of carbon dioxide and climatic conditions will also affect the inter-seasonal distribution of crop yields. Thus, a sectoral model which considers changes in the temporal distribution of yields has significant merit for examining the impacts of environmental changes.

The stochastic agricultural sector model has intuitive appeal. Acreage decisions are dependent on an empirical distribution of crop yields and known demand relationships. Processing and consumptive decisions, on the other hand, are conditional upon realized yields (*i.e.*, state of nature). Agricultural production may be used as an intermediate good or consumed as a final product. A particular advantage of the model formulation is that it provides a distribution of prices, production, revenue, and surplus measures. However, extreme care must be exercised when interpreting these distributions because results are sensitive to assumptions in model formulation and scenario design.

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A brief review of the effects of carbon dioxide and climate on crop growth and yield is warranted before commenting further on the analysis.[2] The major climatic factors which determine crop yields are temperature, precipitation, and solar radiation. Solar radiation is a measure of light energy available to the crop to carry on the process of photosynthesis. The capacity of the plant to use this available energy to accumulate harvestable biomass depends on leaf area development and the duration of the growing season. These two factors are critically dependent on temperature. In many regions, warmer temperatures would reduce crop yields. On the other hand, crop production in more northerly locations may benefit from warmer temperatures by lengthening the growing season. Perhaps the most crucial factor which lowers yields is the lack of water. Low soil moisture inhibits leaf growth which means slower grow rates and lower yields. The degree of impact of warmer temperatures and precipitation changes will.vary by location and crop (see *e.g.*, Wilks, and Liverman *et al.*).

Increases in carbon dioxide will be advantageous for plant growth through higher rates of photosynthesis and lower rates of transpiration (Acock). Increased CO_2 around the plant leaf causes stomates to partially close which reduces transpiration from the leaf. The reduction in the rate of water loss coupled with higher rates of photosynthesis results in greater water use efficiency (biomass accumulated per unit of water transpired). The rate of photosynthesis is dependent on the relative concentration of CO_2 and O_2 in the leaf. Higher concentrations of CO_2 will increase photosynthesis. Crop species classified as C_4 crops (*e.g.*, corn, sorghum, and sugarcane) have a mechanism which already increases the concentration of CO_2 at the site of photosynthesis. C_3 crops (*e.g.*, wheat, rice, cotton, soybeans, and alfalfa) do not have a similar

[2]Kimball *et al.* provide a general discussion of the effect of carbon dioxide and climate on plant growth which is accessible to non-agronomists.

mechanism, therefore, the concentration of CO_2 in the leaf is dependent upon the ambient CO_2 concentration. Consequently, the projected increase in ambient CO_2 is expected to cause a substantially greater increase in the rate of photosynthesis in C_3 plants as compared to C_4 plants.[3] Hence, the direct effects of CO_2 on crop yields will also vary across crops.

Economic analysis is sensitive to scenarios of climate change because the effect on the distribution of crop yields of warmer temperatures may be offset by increased precipitation and the direct effects of higher CO_2. Park and Sinclair demonstrate that the impact of warmer temperatures on the moments of the distribution of corn yields at Urbana, Illinois may be directly offset by increased precipitation. They found that a warmer, drier climate would tend to be associated with lower average yields and a flatter, more symmetric yield distribution. Interestingly, the effects of higher ambient CO_2 on the moments of the distribution is directly opposite to the effects of warmer temperature (Park and Moss). Increased CO_2 tends to increase the mean, variance, and skewness. The fact that the EPIC crop simulations reveal that climate change will tend to increase average yields and reduce the standard deviation is consistent with the direct effects of CO_2 and increased rainfall offsetting the effects of warmer temperatures, and the increased rainfall reducing the variance of dryland yields. Also, the fact that cotton and soybean yields exhibited higher standard deviations in most regions agrees with results suggesting that the variability of C_3 crops relative to C_4 crops may substantially increase (Park and Moss). The GISS and GFDL scenarios each predict an increase in annual rainfall. Although the temperature changes depicted in the GFDL may be too extreme, recent studies

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[3]In the Calvin cycle (C_3 cycle), CO_2 is metabolized to produce sugar and starch. C_4 plants have a precursor pathway to concentrate CO_2 at the CO_2-fixing enzyme, and thereby allow higher rates of photosynthesis. Therefore, C_4 plants tend to be higher yielding than C_3 plants at lower concentrations of atmospheric CO_2. C_3 crops include wheat, rice, cotton, soybeans, and alfalfa. C_4 crops include corn, sorghum, and sugarcane.

have suggested that the summer drying in the GFDL scenario may be more appropriate than the GISS scenario for North America (Houghton, Jenkins, and Ephraums). If the climate in the major crop production areas became drier the model would likely suggest that the variability of most prices would increase rather than decrease. Consequently, the economic implications must be interpreted with respect to the particular climate scenario assumed.

The results will also be sensitive to the manner in which the states of nature are determined from the assumed climate changes. McCarl *et al.* use the EPIC model to simulate yields of five crops--cotton, corn, soybeans, wheat, and sorghum. The impacts of CO_2 and climate changes on yields of the other seven crops in the model were inferred from the average change in the five simulated crops. However, two of the simulated crops are C_4 crops (corn and sorghum) which will have a lower response to increased CO_2 than the others. One is a C_3 legume (soybeans) which will have an even greater response than other C_3 plants. A more appropriate approach would be to infer changes in yields of the non-simulated crops from the crops most similar. For example, the effects of environmental changes on yields of rice, barley, oats are likely to be most similar to the effects on simulated wheat yields. Sugarcane yield responses to changes are likely to be most similar to the response of simulated corn yields. Because of the differences in physiology, the competition between C_3 and C_4 crops could alter significantly as atmospheric CO_2 continues to increase and gradual changes in climate occur. Therefore, a careful analysis of the impacts of global climate change should recognize the differences among crops.

Another issue is the time period selected as the base scenario. The years 1977-1989 incorporate some of the most variable production years with droughts in 1980, 1983, and 1988 growing seasons. Selection of an alternative time period may provide a vastly different distribution, and it is unclear which period would provide the most appropriate empirical distribution. Extending the data series may provide a more representative empirical distribution, but would add to the computational cost. A related issue is the specification of changes in the distribution of weather variables. Some have suggested that the variability of weather would increase. Two alternative approaches have been used to handle differences in the distribution of weather variables. One is to use an analog period such as the 1930's to provide weather data consistent with the expected climate. Another is to use stochastic weather generator to simulate weather data consistent with specified distributional parameters (Kaiser *et al.*). Nonetheless, the analysis is conditional upon the assumed weather patterns.

The global nature of the changes also need to be acknowledge. It appears that the analysis has assumed no changes in the foreign sector. However, increasing levels of CO_2 and climate changes are a global phenomenon. Tobey, Reilly, and Kane demonstrate the potential for adjustments in worldwide production of traded crops to reduce the impact of climate change on agricultural sector. It is unclear whether the net effect of the changes on the rest of the world will be zero as assumed.

Although there are some limitations to the analysis presented, the paper provides a step towards a greater understanding of the aggregate effects of global changes on the U.S. agricultural sector. The results illustrate the need to assess the impacts on the distribution of crop yields, and provides a way to determine the implications of changes for distribution of prices, production, and welfare of the agricultural sector. A sector analysis of this type should complement the on-going research in the area of global climate change.

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MODELLING RISK RESPONSE IN THE BEEF MARKETING CHANNEL:

A MULTIVARIATE GENERALIZED ARCH-M APPROACH

by

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MODELLING RISK RESPONSE IN THE BEEF MARKETING CHANNEL: A MULTIVARIATE GENERALIZED ARCH-M APPROACH

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Abstract

A model of the farm-retail price spread for beef is specified under rational expectations, in which systematic risk response on the part of marketing intermediaries is allowed. This leads to a three-equation structural model containing potentially time-varying risk terms in margin and supply equations, which I approximate and estimate using a multivariate GARCH-in-Mean approach. The estimated model is then used to infer relative risk premia in beef margins, and to simulate short-run equilibrium risk effects. Results indicate that price risk has, at times, had substantial impacts on farm and retail beef prices and production.

Keywords: beef market, farm-retail margins, GARCH-M models, margins, price risk, rational expectations.

Following the pioneering work of Behrman and Just, numerous studies have attempted to quantify the role of risk in agricultural supply equations (Antonovitz and Green; Aradhyula and Holt). More recently, the effect of risk on marketing margins of agricultural products has been examined. Using a variant of Sandmo's model of the firm under output price uncertainty, Brorsen et al. show that marketing channel intermediaries also may be impacted by output (demand) price risk. Brorsen et al.'s model has been extended by Schroeter and Azzam to allow for possible noncompetitive behavior on the part of marketing firms.

More work on this topic is required. First, prior studies have not recognized that, in an expected utility framework, expectations must be taken with respect to <u>both</u> the mean and variance of output price. Accordingly, the appropriate dependent variable in a risk-responsive margin equation is the <u>expected</u> price spread, as opposed to the observed spread as used previously. There also is a need to refine procedures for inferring risk response in margin equations. Brorsen et al. and Brorsen, Chavas, and Grant used fixed-weight moving average methods to estimate risk effects. Although employed extensively, simple extrapolative techniques may provide inaccurate results (Pagan and Ullah). Alternatively, Schroeter and Azzam used an ARCH (autoregressive conditional heteroskedasticity) model. The ARCH approach is a clear improvement over <u>ad hoc</u> extrapolative procedures; Schroeter and Azzam, however, did not estimate the ARCH process simultaneously with their model's structural equations. As a result, the process generating price variability is not endogenous in their model.

The primary objective of the present article is to determine the role of risk in the beef marketing channel. Like Schroeter and Azzam, I use a generalized ARCH (GARCH) process to estimate risk response in a farm-retail margin equation. I go beyond their approach, however, in allowing the structural model's conditional covariance matrix to be time varying. That is, my model treats risk as endogenous because the multivariate GARCH process used to infer risk response is estimated simultaneously with the structural equations. This study also parallels Brorsen, Chavas, and Grant in that, in addition to estimating retail demand and farm-retail margin equations, I endogenize beef production (primary supply). Inasmuch as short-run beef supply responds to (farm) price risk (Antonovitz and Green), I am able to assess market equilibrium risk impacts in the beef marketing channel.

Under risk aversion and output price uncertainty, the appropriate dependent variable in the margin equation is the expected price spread. I obtain _ex ante_ expectations of the mean and variance of retail price using rational-expectations (Diebold and Pauly). Because of the associated nonlinear cross-equation restrictions, the resulting model is a type of multivariate GARCH-in-Mean (GARCH-M) model.[1/] Engle, Lilien, and Robins, Diebold and Pauly, and others have found strong GARCH-M effects in high-frequency, univariate, structural, and non-structural models; this study, however, reports the first application of the GARCH-M approach to a multivariate structural system.

The focus on the beef marketing channel also is of interest. For the past twenty years, beefpacking plants increasingly have combined slaughter and processing operations, with the effect that over 90% of beef is now sold in boxed (fabricated) form (Johnson et al.). Unlike with carcass beef, comparatively little use is made of contracting or formula pricing in the boxed beef market (Ward). Moreover, there are no futures markets for boxed beef which could allow marketing intermediaries to spread price risks. These reasons, along with the high sales volume, low-margin character of the beefpacking industry, suggest that the beef marketing channel may be quite sensitive to meat price variability (Ward, p. 170).

Conceptual Framework

Following Gardner and others, I assume market intermediaries operate effectively in a competitive environment. The present model differs from previous versions, however, in that packer-processors are assumed to form rational-expectations of output price and price risk.

Assume that m firms purchase a raw farm input, x, and transform it into a food product, q.[2/] Other inputs, $\underline{z}$, also are used in the production of q. Moreover, q is produced using fixed proportions of x, the raw farm input; but other inputs, $\underline{z}$, can be used in variable proportions. Under these assumptions, each firm's technology can be represented by a Leontief-type production function

$$(1) \qquad q = \min[x/k,\ g(\underline{z})],$$

where k is a positive proportionality constant. Letting w denote farm product price, and $\underline{r}$ the price of other inputs, the cost function associated with (1) is

$$(2) \qquad C(w,\ \underline{r},\ q) = \min_{x,\underline{z}}[wx + \underline{r}'\underline{z} \mid \text{s.t. } (1)] = wkq + \underline{r}'\underline{z}^{*}(\underline{r},\ q),$$

where $x^{*}(w,\ q) = kq$ and $\underline{z}^{*}(\underline{r},\ q)$ are cost-minimizing input demands for, respectively, farm and non-farm inputs. C is linear homogeneous, increasing, and concave in (w, $\underline{r}$); and increasing and convex in q. Firm profit is then given by

$$\pi = (p - kw)q - \tilde{C}(r,\ q)$$

where $\tilde{C}(r,\ q) = \underline{r}'\underline{z}^{*}(\underline{r},\ q)$ denotes the cost function of nonfarm inputs.

Firms face a random (inverse) demand schedule

$$(3) \qquad p = \bar{p}(Q,\ \underline{s}) + \gamma\tilde{\epsilon}_1,$$

where Q = mq is industry output; $\underline{s}$ is a vector of exogenous demand shifters; and

$\tilde{\epsilon}_1$ is a random variable, where $E(\tilde{\epsilon}_1) = 0$ and $E(\tilde{\epsilon}_1^2) = 1$. Expected market price is then given by $E(p) = \bar{p}(Q, \underline{s})$ and retail price variance by $Var(p) = \gamma^2$.

Under risk aversion, each firm's goal is to maximize expected utility of profit. Each packer-processor's objective is therefore characterized by

$$(4) \qquad \max_q Eu[(p - kw)q - \tilde{C}(\underline{r}, q)],$$

where $u(\pi)$ is a von Neumann-Morgenstern utility function with $du/d\pi > 0$ and $d^2u/d\pi^2 < 0$ under risk aversion. Expectations are taken with respect to the random variable, retail price. The first-order condition associated with (4) is

$$(5) \quad E[u'((p - kw) - \tilde{c}(\underline{r}, q))] = \bar{p}(Q, \underline{s}) - kw - \tilde{c}(\underline{r}, q) + Cov(u',p)/Eu' = 0,$$

where $\tilde{c}(\underline{r}, q) = \partial\tilde{C}(\underline{r}, q)/\partial q$ and $Cov(u',p) = \rho(\gamma^2 \cdot E[u' - Eu']^2)^{1/2}$ is the covariance between marginal utility and expected price, ρ being the correlation between u' and p. Equation (5) can be solved to obtain the firm's supply function. Alternatively, this firm-level supply equation can be inverted to obtain an expression for the expected farm-retail margin (Brorsen et al.)

$$(6) \qquad \bar{p}(Q, \underline{s}) - kw = \tilde{c}(\underline{r}, q) + \delta^*\gamma,$$

where $\delta^* = -(Eu')^{-1}\rho(E[u' - Eu']^2)^{1/2}$.

Because under risk aversion output price and marginal utility of profit are negatively correlated (Baron), δ^* will be positive for risk averse firms. Brorsen et al. show that under decreasing absolute risk aversion (DARA), a marginal increase in output price risk will increase the expected marketing margin. Also, because of the fixed factor of proportionality, kw is farm input price expressed in units equivalent to $\bar{p}$.

Assuming the industry behaves like a representative firm, the aggregate expected margin equation (e.g., inverse aggregate packer-processor supply) is

$$(7) \qquad \bar{M} = \bar{p}(Q, \underline{s}) - kw = \Pi(\underline{r}, Q) + \delta_1\gamma + \epsilon_2,$$

where $\bar{M}$ denotes expected margin and a stochastic term, ϵ_2, has been added as a prelude to econometric specification.[3/] Brorsen et al. show that under DARA, $\partial\bar{M}/\partial Q > 0$ and $\partial\bar{M}/\partial r_j \geq 0$ (≤ 0) as $\partial Q/\partial r_j \geq 0$ (≤ 0).

Empirical Issues

Before proceeding, several issues regarding retail price expectations and time-varying risk measures must be addressed. To begin, equation (7) shows that it is the difference between expected output price and farm price (i.e., the expected margin) that serves as the dependent variable in a margin equation with retail price uncertainty. Brorsen et al., Brorsen, Chavas, and Grant, and Schroeter and Azzam used the observed margin as the dependent variable. Although this substitution seems innocuous, the econometric implications are significant. If the observed margin is used in place of the expected one in (7), the margin equation's error process coincides with that of the (inverse) demand function. In other words, $\epsilon_{2t} = \gamma\tilde{\epsilon}_{1t}$, where a t subscript has been added to denote time[4/]. Alternatively, ϵ_{2t} could be a separate error term (ϵ_{2t} is the result of errors in approximation and other factors); but appropriate estimates can be obtained only by using the composite error term $\lambda_t = \epsilon_{2t} + \gamma\tilde{\epsilon}_{1t}$ when ex post output price is used in (7).[5/] Either way, the margin equation's error process depends on the demand equation's error process when observed output price is used in lieu of expected output price. This issue has not been explored in previous research.

Conversely, a method could be identified for directly determining ex ante expectations of output price and, consequently, expected margins. Such a method would preferably be consistent with the retail demand specification. In other words, output price expectations could be determined according to the rational expectations hypothesis (REH). The REH has appeal because if output price is the primary "unknown" and is the underlying source of packer-processor uncertainty, it is logical to estimate price expectations in a manner consistent with the specification of primary demand.

The REH can also be used to model ex ante expectations of price variance (Aradhyula and Holt; Antonovitz and Green). Of course, this requires the model's forecast error variances be time varying. In recent years, ARCH and GARCH models have been used to estimate time-varying conditional variances in single- (Bollerslev 1986) and multi-equation (Bollerslev 1990; Baillie and Myers) setups. GARCH (ARCH) models have appeal because they provide a time-series rationale for time-varying conditional variances. The GARCH (ARCH) approach to modelling second moments also is consistent with the REH because the information set, including lagged realizations and innovations of endogenous variables, coincides with that commonly used to form expectations of the mean (Diebold and Pauly).

Defining $\epsilon_{1t} = \gamma\tilde{\epsilon}_t$, a GARCH(p,q) process consistent with equation (3) is

$$\text{(8)} \qquad \text{Var}(\epsilon_{1t}|\psi_{t-1}) = h_{1t} = \omega_0 + \sum_{j=1}^{q} \alpha_j\epsilon_{1t-j}^2 + \sum_{j=1}^{p} \beta_j h_{1t-j},$$

where $\omega_0 > 0$ and $\alpha_j \geq 0$, $\beta_j \geq 0$ for all j; and ψ_{t-1} is the information set generated by all available information through time t-1. If $\beta_j = 0$ for all j, then (8) reduces to an ARCH(q) process. The square root of one-step-ahead predictions from (8) replace γ in (7) when estimating risk response in margin equations. The resulting model is a multivariate GARCH-M (ARCH-M) model because, under the REH, not only are demand and margin equation parameters shared, but parameters of the demand equation's GARCH (ARCH) process also are shared. Thus, the structure generating price risk is endogenous in a GARCH-M model.

Econometric Methodology

The preceding discussion suggests that risk effects in the beef marketing channel can be modeled with a GARCH-M framework. The present section outlines estimation procedures when the model's conditional covariance matrix is time varying, focusing on Bollerslev's (1990) constant conditional correlations model.

Bollerslev's (1990) setup holds conditional correlations among endogenous variables constant, but allows time-varying conditional covariances. Define $\underline{y}_t$ as an (N x 1) vector of endogenous variables, $\underline{\epsilon}_t$ as a corresponding (N x 1) vector of innovations, and h_{ijt} as the ij'th element of $H_t = Var(\underline{\epsilon}_t|\psi_{t-1})$. The conditional covariance between the i'th and j'th elements of $\underline{\epsilon}_t$ (i.e., ϵ_{it} and ϵ_{jt}) is

$$(9) \qquad h_{ijt} = \rho_{ij}(h_{iit}h_{jjt})^{1/2}, \; i = 1,\ldots,N, \; j = i+1,\ldots,N,$$

where $\rho_{ij} = Corr(\epsilon_{it},\epsilon_{jt}|\psi_{t-1})$, the conditional correlation coefficient; $\rho_{ij} \in [-1,1]$ for all i and j; and $\rho_{ii} = 1$ for all i. The diagonal elements of H_t—defined as $h_{iit} = \sigma^2_{it} > 0$ for all i and t—are given by specifications similar to (8). In general ρ_{ij} could be time varying; but if ρ_{ij} is constant for all t, considerable simplifications arise in estimation and inference.

To see this, rewrite the conditional covariance matrix H_t as $H_t = D_t\Lambda D_t$, where D_t denotes an (N x N) diagonal matrix with elements $\sigma_{1t},\ldots,\sigma_{Nt}$, and Λ is an (N x N) time-invariant, symmetric, positive definite matrix, where $\{\Lambda_{ij}\} = \rho_{ij}$. Assuming conditional normality, the log likelihood function is

$$(10) \; L(\varphi) = -\frac{TN}{2}\log 2\pi + \sum_{t=1}^{T}\log||J_t|| - \frac{T}{2}\log|\Lambda| - \sum_{t=1}^{T}\log|D_t| - \frac{1}{2}\sum_{t=1}^{T}\hat{\underline{\epsilon}}_t'\Lambda^{-1}\hat{\underline{\epsilon}}_t,$$

where $\hat{\underline{\epsilon}}_t = D_t^{-1}\underline{\epsilon}_t$ is an (N x 1) vector of standardized residuals, T is sample size, J_t is the Jacobian of the system, and φ represents all unknown parameters in $\boldsymbol{\epsilon}_t$ and H_t. Under standard regularity conditions the maximum likelihood (ML) estimate of φ is asymptotically normal. Unlike other multivariate GARCH (ARCH) setups though, only one (N x N) matrix inversion is called for during each evaluation of (10). Also, $\log|D_t| = \sum_{i=1}^{N} \log \sigma_{it}$. I use Broyden's algorithm, along with numerical derivatives, in the maximization of (10) to estimate a multivariate GARCH-M model for the beef marketing channel.

Data and Model Specification

My application is to a three-equation model of the beef market, including equations for retail demand, (expected) farm-retail margin, and short-run beef supply. Although my primary focus is on determining risk response in the beef marketing channel, there is substantial evidence that short-run cattle supplies react to current farm price (Jarvis) and, perhaps, to current (farm) price risk (Antonovitz and Green). In a short-run model, it is therefore necessary to endogenize beef supply. By including a measure of farm price risk in the supply equation, the relative importance of risk in short-run beef supply also can be assessed vis-a-vis the marketing margin.

Data analyzed are monthly, 1970-89. Using monthly data facilitates estimation of risk effects, inasmuch as beef inventories are seldom held for extended periods of time and because it is often easier to identify conditional heteroskedasticity with higher-frequency data; monthly data, however, do add dynamic complexities.

Retail beef demand is specified in price-dependent form as

$$(11)\quad \Delta RPB_t = \gamma_0 + \gamma_1 \Delta QB_t + \gamma_2 \Delta QB_{t-1} + \gamma_3 \Delta QB_{t-2} + \gamma_4 \Delta RPP_t + \gamma_5 \Delta INC_t + \gamma_6 \Delta INC_{t-1}$$

$$+ \gamma_7 \Delta INC_{t-2} + \gamma_8 \Delta INC_{t-3} + \gamma_9 D79 + \gamma_{10} ZRPB_{t-1} + \gamma_{11} SIN1 + \gamma_{12} COS1$$

$$+ \gamma_{13}SIN2 + \gamma_{14}COS2 + \sum_{j=1}^{11} \gamma_{14+j}\Delta RPB_{t-j} + \epsilon_{1t},$$

where Δ is a first-difference operator; RPB_t is retail beef price, in cents per lb.; QB_t is commercial beef production, in million pounds; RPP_t is retail pork price, in cents per lb.; INC_t is personal disposable income, in billion dollars; D79 is a dummy variable equal to zero prior to 1979, and one thereafter; SIN1-COS2 are harmonic variables for six- and twelve-month cycles; and $\gamma_0,\ldots,\gamma_{25}$ are parameters.[6/] All beef prices were obtained from White et al. Retail pork prices and beef production were collected from Livestock and Meat Statistics. Income data were collected from various issues of the Survey of Current Business. All prices and income are deflated by the Consumer Price Index (CPI) (1967 = 1.0), collected from the Survey of Current Business. Retail demand is specified in first-difference form because Phillips-Perron tests fail to reject the null hypothesis of a unit root in (real) retail beef prices.[7/]

The (inverse) retail demand equation includes current and lagged changes in beef production. Lagged production is relevant if retail beef prices respond gradually to quantity changes. The change in retail pork price is included because pork is a substitute for beef. Current and lagged changes in disposable income capture income effects in beef demand. D79 is included to capture the apparent break in the drift of nonstationary retail beef prices that occurred during the later half of the sample period. The eleventh-order lag specification for ΔRPB_t captures short-run retail price dynamics.

Because variables RPB_t, RPP_t, and INC_t in the retail price equation are integrated of order one or I(1), there may exist one or more linear combinations (cointegrating vectors) of these variables that are I(0). In the event, it is useful to specify the retail price equation as an error correction model (ECM), in which a term, $ZRPB_{t-1}$, associated with departures from long-run equilibrium is included. Using Johansen's procedure, I find at most one unique cointegrating vector associated with the respective I(1) variables (table 1). Point estimates of coefficients of the (normalized) eigenvector corresponding to the largest eigenvalue, also reported in table 1, are used to construct the error correction term $ZRPB_{t-1}$ in the ECM for retail beef price.[8/]

The specification of the (expected) farm-retail margin equation consistent with (7), where $\Pi(\underline{r}, Q)$ is approximated with a linear form, is

$$(12)\quad \bar{M} = \theta_0 + \delta_1\sigma_{1t} + \theta_1 QB_t + \theta_2 PE_t + \theta_3 WR_t + \theta_4 D79 + \theta_5 SIN1 + \theta_6 COS1$$

$$+ \theta_7 SIN2 + \theta_8 COS2 + \sum_{j=1}^{12} \theta_{8+j} MRG_{t-j} + \epsilon_{2t},$$

where,

$$\bar{M} = E(RPB_t|\psi_{t-1}) - FPB_t,$$

and where $E(RPB_t|\psi_{t-1})$ denotes the rational expectation of retail beef price, in cents per lb.; FPB_t is farm beef price in retail equivalents (net of by-byproduct value), in cents per lb.; σ_{1t} is the rational expectation of the standard deviation of (real) retail beef price; PE_t is an indexed energy price; WR_t is the meat packing wage rate, in dollars per hour; MRG_{t-j} denotes the lagged (realized) farm-retail margin; and $\Theta_0,\ldots,\Theta_{20}$ and δ_1 are parameters. Phillips-Perron tests indicate the null hypothesis of a unit root can be rejected for the (real) farm-retail margin; equation (12) is thus specified in the levels of the data. The energy price index was acquired from the Survey of Current Business and wage rate data were obtained from Employment and Earnings. Prices are deflated by the CPI.

The rational expectation of the time-varying standard deviation σ_{1t} of retail price measures the effect of output price risk on the farm-retail margin.

Beef production, QB_t, is included because, as suggested by theory, production levels should affect the expected margin. Prices of energy and labor reflect important input costs in beefpacking and processing, and harmonic variables are included to capture seasonality. D79 is included to account for the apparent break that occurred in farm-retail margins following 1979. The twelfth-order lag specification allows for short-run dynamic adjustments in the margin equation.

Short-run beef production is specified as

$$(13)\quad QB_t = \nu_0 + \nu_1 FPB_t + \delta_2\sqrt{h_{22t}} + \nu_2 PCO_t + \nu_3 OFD_{t-1} + \nu_4 D79 + \nu_5 SIN1 + \nu_6 COS1 + \nu_7 SIN2 + \nu_8 COS2 + \sum_{j=1}^{12} \nu_{8+j} QB_{t-j} + \epsilon_{3t},$$

where $\sqrt{h_{22t}}$ is the time-varying conditional standard deviation of (real) farm beef price; PCO_t is the price of corn paid by farmers, in dollars per bushel; OFD_t is cattle on feed in seven states, in thousand head; and $\nu_0, \ldots, \nu_{20}$ and δ_2 are parameters. Corn prices were obtained from Agricultural Prices and cattle on feed data were collected from Livestock and Meat Statistics. As before, all prices are deflated by the CPI.

Beef supply is specified in the levels of the data because Phillips-Perron tests reject the null hypothesis of a unit root in QB_t. Both current farm price and price risk can influence short-run beef supply (Jarvis), and corn is an important input cost in fed beef production. The available stock of marketable (fed) cattle is reflected by last period's cattle on feed numbers. As before, D79 is included to allow for the break in the data following 1979. The twelfth-order lag specification for QB_t captures short-run supply dynamics.

The expected farm-retail margin, obtained according to the REH, is the left-hand-side variable in (12). Because short-run beef supply depends on farm price, the rational-expectation reduced forms for the mean and standard deviation of retail price are complicated beyond those outlined in preceding sections. Details on obtaining the model's final form are available upon request. In general though, $E(RPB_t|\psi_{t-1})$ will depend on expectations of retail pork price, disposable income, energy price, meatpacking wage rate, and corn price.

Expectations of exogenous variables are obtained using a vector autoregression representation (VAR). Because unit root tests indicate all contemporaneously exogenous variables are I(1), the auxiliary VAR is specified in first-difference form. Moreover, the VAR may include error correction terms if the underlying variables are cointegrated. Johansen's cointegration tests indicate there is at most one cointegrating vector associated with (real) retail pork price, disposable income, energy price, meatpacking wage rate, and corn price. The auxiliary vector error correction model (VECM) is thus specified as

$$\Delta\underline{X}_t = \sum_{i=1}^{k-1} \Gamma_i \Delta\underline{X}_{t-i} + \Pi\underline{X}_{t-k} + \Phi\underline{S}_t + \underline{\mu} + \underline{\varepsilon}_t \qquad (t = 1,\ldots,T), \tag{14}$$

where $\underline{X}_t = (RPP_t, INC_t, PE_t, WR_t, PCO_t)'$; $\underline{S}_t = (SIN1, COS1, SIN2, COS2)'$; Γ_i is a 5 x 5 parameter matrix, $i = 1,\ldots,k-1$; $\Pi = \underline{\alpha}\underline{\beta}'$ is a 5 x 5 matrix conveying the long-run information in the data, where $\underline{\beta}$ is a 5 x 1 cointegrating vector and $\underline{\alpha}$ a 5 x 1 vector of "error correction" parameters; Φ is a 5 x 4 parameter matrix; $\underline{\mu}$ is a 5 x 1 vector of constant terms; and $k = 5$. With predictions generated from ML estimates of the VECM in (14), $E(RPB_t|\psi_{t-1})$ can be evaluated.

Finally, preliminary analysis indicated GARCH(1,1) processes for h_{11t}, h_{22t}, and h_{33t} were adequate for specifying H_t. The conditional variance-covariance structure for the three-equation GARCH-M model in (11)-(13) is then

$$h_{iit} = \omega_i + \alpha_{i1}\,\epsilon^2_{it-1} + \beta_{i1}\,h_{iit-1}, \tag{15}$$

$$h_{ijt} = \rho_{ij}(h_{iit}h_{jjt})^{1/2}, \quad i,j = 1\ (RPB_t),\ 2\ (\bar{M}_t),\ 3\ (QB_t),\ i \neq j.$$

Estimation Results

ML estimates of the rational-expectations GARCH-M model of the beef marketing channel are reported in table 2. Short-run flexibilities and elasticities of key exogenous variables, at data means, are recorded in table 3. Several model diagnostics are presented in table 4.

Point estimates of α_{i1} and β_{i1}, i=1,2,3, are positive and individually significant (table 2), indicating the presence of conditional heteroskedasticity in error terms of the structural equations. Further evidence of conditional heteroskedasticity is obtained by restricting $\delta_1 = \delta_2 = 0$ and estimating the model that nests the homoskedastic specification. Conditional on $\delta_1 = \delta_2 = 0$, the resulting Likelihood Ratio (LR) test statistic of $\alpha_{i1} = \beta_{i1} = 0$, i=1,2,3, is 144.364, a value of an asymptotic $\chi^2(6)$ distribution under the null hypothesis. The homoskedastic model is thus rejected at any reasonable level.[9] In all cases, the unconditional variances, $\hat{\omega}_i/(1 - \hat{\alpha}_{i1} - \hat{\beta}_{i1})$, are defined because $\hat{\alpha}_{i1} + \hat{\beta}_{i1} < 1$ for all i.

Estimates of the conditional correlation parameters also are individually significant. The LR test statistic for $\rho_{ij} = 0$ for all i ≠ j is 98.848, which asymptotically under the null hypothesis is the realization of a $\chi^2(3)$ distribution. This overwhelming rejection of independence indicates short-run beef prices and production are significantly correlated, the conditional correlation with farm and retail prices (-0.716) being the strongest.[10]

Conditional variances and covariances are plotted for the sample period in figure 1. Of interest is that the conditional variance of the expected margin generally exceeds that of retail price, indicating more volatility in farm prices than retail prices. Furthermore, figure 1 shows variances and covariances were generally much more volatile during the 1970s, and were especially large during the mid-1970s. Although the model provides no structural explanation of the extreme price volatility observed in the beef market during the 1970s, this period was associated with wage and price controls, unstable grain and energy prices, and high and variable inflation rates.

Retail demand equation results show that all coefficients of current and lagged beef production are significant (table 2). As might be expected, the short-run retail price flexibility of beef production is small (-0.08) (table 3). The effect of retail pork price on retail beef price is positive and significant, with a short-run flexibility of 0.09. Disposable income also has a positive relationship with retail beef price, its short-run flexibility being about 0.13 (table 3). The point estimate of the error correction parameter, γ_9, is negative and significant.

Turning to the margin equation, note that all economic variables are significant at usual levels (table 2). Of interest is that the point estimate of δ_1, the marginal effect of (expected) retail price risk on (expected) farm-retail margins, is positive and highly significant. This result is consistent with theory and provides evidence that beefpacker-processors react adversely to output price risk. The corresponding short-run (expected) farm-retail price spread flexibility with respect to retail price risk is 0.09 (table 3).

Other economic variables in the margin equation have plausible signs and magnitudes. For instance, beef production has a positive and significant relationship with the expected margin, its short-run flexibility being about 0.12. Energy prices and wage rates also have a positive and significant effect on expected short-run farm-retail margins (table 2), the respective flexibilities being 0.18 and 0.36 (table 3).

Estimates of beef supply parameters also are plausible. For example, short-run beef supply has a significant, negative relationship with current farm price and a positive relationship with farm price risk. These results are consistent with Jarvis' theory of cattle supply, where cattle are viewed as both a consumption and investment good. Short-run own price and risk elasticities (-0.30 and 0.01, respectively) are comparable with previous estimates (e.g., Antonovitz and Green). Short-run beef supply has a significant, positive relationship with corn price and with (lagged) cattle on feed (table 2).

Several diagnostic tests are reported in table 4. First, skewness and kurtosis estimates of each standardized residual series do not indicate significant departures from normality. Tests of up to 24th-order serial correlation signify only limited evidence of remaining autocorrelation in the standardized residuals. Similarly, tests of 24th-order serial correlation in the squared standardized residuals are in the acceptable range (table 4).

As an added check, Pagan-Sabau consistency tests are employed. These tests determine if the conditional variances are consistent with the second-moment pattern of the residuals, and require estimating OLS regressions of the type

$$\hat{\epsilon}_{it}\hat{\epsilon}_{jt} = b_{ij0} + b_{ij1}\hat{h}_{ijt}, \quad i,j=1,2,3,$$

where, under the null hypothesis of model consistency, b_{ij1} should not differ significantly from unity. T-statistics of the null hypothesis $b_{ij1} = 1$, obtained using White's correction for heteroskedasticity, are reported in the lower panel of table 4. In all cases, the t-statistics are insignificant at the 5% level, indicating the conditional variance process is consistent.

In summary, the constant conditional correlations model with a GARCH(1,1) conditional variance structure provides a reasonable representation of the conditional variance dynamics in the beef marketing channel.

Assessment of Risk

The estimated GARCH-M model is now used to determine the role and relative importance of risk in the beef marketing channel. This is accomplished by performing an additional test, and by simulating the model to infer time-varying risk premia in the beef marketing channel from 1971 to 1989.

The LR test statistic of 26.008 for $\delta_1 = \delta_2 = 0$ is significant in the $\chi^2(2)$ distribution at all usual levels, indicating risk terms are jointly significant in beef margin and supply equations. Furthermore, the risk elasticity of 0.088 in the margin equation is over six times larger than the corresponding risk elasticity of 0.014 in the supply equation (table 3). This result is meaningful because it provides strong evidence that risk impacts, as gauged by elasticities, are of potentially <u>greater</u> importance in the beef margin equation than in the beef supply equation. Qualitatively similar results in the rice market were obtained by Brorsen, Chavas, and Grant.

The preceding results show that price risk is important at several beef market levels; they say nothing, however, about how risk has influenced market performance. The importance of risk in the margin equation is evaluated by computing $RRP_t = \hat{\delta}_1\sigma_{1t}/[E(RPB_t|\psi_{t-1}) - FPB_t]$, the implied relative risk premium. Results, graphed in figure 2, range from a peak of 24.4% to a low of 4.3%, the average being 8.7%. A break in the ratio occurred between 1979 and 1981, then it stabilized around 5% after 1981. On balance, the risk premium in the farm-retail beef margin equation is certainly non negligible.

Such results bracket the role of risk in beef marketing margins. But they do not <u>per</u> <u>se</u> indicate how risk affects short-run equilibrium prices and quantity. To assess combined effects of retail and farm price risk on prices and production, I simulate the model stochastically after setting $\delta_1 = \delta_2 = 0$.

Results, summarized in table 5, show that in all years average farm beef price would have increased in the absence of risk. Big impacts were recorded in the 1970s, when beef prices were generally more volatile than before or after (figure 1). During 1971-89, for example, farm prices would have been above observed levels by an average of 2.97 cents per retail lb., or 5.90%. Farm-retail price spreads would have been below observed levels by, on average, 8.95%, or 3.05 cents per retail lb. Moreover, average farm-retail margins would have been lower each year, with the implied equilibrium risk premium ranging from 4.2% to 16.6%.

Conclusions

In this paper I have sought to determine the role of risk in the farm-retail price spread for beef. Although previous research has found significant risk effects in price linkage equations of wheat, rice, and pork, similar results have not been reported for beef. Maximum likelihood estimates of retail demand, (expected) farm-retail margin, and beef production equations were obtained using monthly data from 1970 to 1989. The estimated GARCH-M model provides a good fit; parameter estimates have plausible signs and magnitudes; the estimated conditional variance structure indicates substantial GARCH effects; and implied flexibilities (elasticities) are reasonable.

Of interest is that price risk, as measured by the rational expectation of the standard deviation of retail price, is significant in the price spread equation. Furthermore, the short-run risk effect in the margin equation—as measured by risk elasticities—is over six times greater than the short-run risk effect in the supply equation. The implication is that short-run price risk is more important for beef packer-processors than for producers. Yet most research on risk effects in agricultural markets has focused on primary supply.

The impact of risk on the beef market was further evaluated by computing the relative risk premium in the margin equation, and by simulating the model after setting risk terms to zero. Results indicate that price risk has, from time-to-time, had a substantial impact on equilibrium beef prices and production. Consequently, as Johnson et al. argue, risk sharing arrangements, such as a futures contract for boxed beef, could enhance pricing efficiency and performance in beef marketing.

Footnotes

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1/ GARCH-in-Mean simply implies the model's time-varying conditional variance-covariance terms are inputs in the conditional mean equations.

2/ I do not distinguish between beef wholesale and retail functions. This assumption is not overly restrictive because trade in carcass beef has declined in importance (Johnson et al.). I assume, however, that it is packer-processors—as opposed to retailers—that face undiversifiable price risk.

3/ For the implied risk premium $R = \delta^{*}\gamma$ in (6), the term δ^{*} will also vary with γ. In the remainder of the paper I therefore use a first-order approximation $R = \bar{R} + \delta_{1}\gamma$ to R, where $\bar{R}$ is an unspecified constant term.

4/ This follows by solving (3) for $\bar{p}$ and substituting the result into (7).

5/ See Mishkin for a discussion of the econometric implications associated with single-equation models of real interest rates that use _ex post_ realizations of inflation in lieu of rational expectations of inflation on the left-hand-side, and thus are associated with composite error terms.

6/ The harmonic variables are SIN1 = $\sin(2\pi t/6)$, COS1 = $\cos(2\pi t/6)$, SIN2 = $\sin(2\pi t/12)$, and COS2 = $\cos(2\pi t/12)$, $t = 1,\ldots,T$.

7/ Results of the unit root tests are available upon request.

8/ The constructed variable $ZRPB_t$ was subjected to the same unit root tests applied to the original data. I accordingly reject the hypothesis that the linear combination of the three I(1) variables contains a unit root.

9/ The LR test statistic for the null hypothesis $\delta_1 = \delta_2 = 0$ and $\alpha_{i1} = \beta_{i1} = 0$, $i=1,2,3$, is 170.372, an extreme value in the $\chi^2(8)$ distribution.

10/ A negative value for $\hat{\rho}_{12}$ reflects a positive correlation with RPB_t and FPB_t in (12), as expected. This hypothesis was confirmed by re-estimating the model after normalizing the margin equation on farm price, in which case an identically large and positive estimate for $\hat{\rho}_{12}$ was obtained.

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Table 1. Cointegration Tests for Real Retail Beef Price, Real Retail Pork Price, and Real Personal Disposable Income.

	Johansen Test Statistics			Normalized Cointegrating Vector		
Test	r = 0	r ≤ 1	r ≤ 2	RPB	RPP	INC
Trace:	32.46 (31.26)	10.01 (17.84)	0.62 (8.08)	1.0	-0.068 (0.136)[a/]	0.066 (0.0003)[a/]
λ_{max}:	22.45 (21.28)	9.39 (14.60)	0.62 (8.08)			

Note: Trace denotes the Johansen likelihood ratio trace test and λ_{max} denotes the maximal eigenvalue test. Values in parentheses are 5% critical values. Results are based on a k = 5 lag specification.

a/ Asymptotic standard error extracted from a Wald test.

Table 2. Maximum Likelihood Estimates of a Rational-Expectations Multivariate GARCH-M Model of the U.S. Beef Sector, 1971-89.

Equation	Parameter	Variable	Coefficient	Standard Error
Retail Demand:[a/]	γ_0	constant	6.203	1.101
	γ_1	ΔQB_t	-0.343	0.091
	γ_2	ΔQB_{t-1}	-0.376	0.105
	γ_3	ΔQB_{t-2}	-0.248	0.079
	γ_4	ΔRPP_t	0.117	0.042
	γ_5	ΔINC_t	0.014	0.008
	γ_6	ΔINC_{t-1}	0.015	0.010
	γ_7	ΔINC_{t-2}	0.008	0.010
	γ_8	ΔINC_{t-3}	0.011	0.009
	γ_9	$ZRPB_{t-1}$	-0.049	0.008
	γ_{10}	D79	0.026	0.157
	γ_{11}	SIN1	-0.117	0.104
	γ_{12}	COS1	0.147	0.106
	γ_{13}	SIN2	0.100	0.118
	γ_{14}	COS2	-0.322	0.122
	$\gamma_{15} - \gamma_{25}$	$\Sigma\ \Delta RPB_{t-j}$	0.327	
Farm-Retail Margin:	θ_0	constant	4.510	2.878
	δ_1	σ_{1t}	2.009	0.325
	θ_1	QB_t	0.208	0.108
	θ_2	PE_t	2.071	0.531
	θ_3	WR_t	3.676	0.676
	θ_4	D79	2.157	0.661

Table 2. (Continued).

Equation	Parameter	Variable	Coefficient	Standard Error
	θ_5	SIN1	0.418	0.151
	θ_6	COS1	0.139	0.138
	θ_7	SIN2	-0.032	0.105
	θ_8	COS2	0.366	0.156
	$\theta_9 - \theta_{20}$	Σ MRG_{t-j}	0.082	
Commercial Production:	ν_0	constant	14.114	1.614
	ν_1	FPB_t	-0.113	0.009
	δ_2	$\sqrt{h_{22t}}$	0.105	0.069
	ν_2	PCO_t	1.166	0.207
	ν_3	OFD_{t-1}	0.245	0.079
	ν_4	D79	-0.587	0.130
	ν_5	SIN1	-0.082	0.045
	ν_6	COS1	-0.080	0.032
	ν_7	SIN2	-0.535	0.094
	ν_8	COS2	-0.338	0.082
	$\nu_9 - \nu_{20}$	Σ QB_{t-j}	0.411	
Retail Price Variance:	ω_1	constant	0.080	0.038
	α_{11}	ϵ^2_{1t-1}	0.195	0.035
	β_{11}	h_{1t-1}	0.767	0.036
Margin Variance:	ω_2	constant	0.322	0.119
	α_{21}	ϵ^2_{2t-1}	0.210	0.057
	β_{21}	h_{2t-1}	0.738	0.049

Table 2. (Continued).

Equation	Parameter	Variable	Coefficient	Standard Error
Production Variance:	ω_3	constant	0.048	0.034
	α_{31}	ϵ^2_{3t-1}	0.186	0.064
	β_{31}	h_{3t-1}	0.728	0.105
Conditional Correlations:	ρ_{12}	constant	−0.716	0.039
	ρ_{13}	constant	0.330	0.066
	ρ_{23}	constant	−0.302	0.066
Log Likelihood:		−1030.237		

Note: For retail demand, $\Sigma\ \Delta RPB_{t-j}$ denotes the sum of the estimated coefficients on (differenced) retail beef prices at lags 1-11. For the margin equation and the production equation, $\Sigma\ MRG_{t-j}$ and $\Sigma\ QB_{t-j}$, respectively, denote the sum of the estimated coefficients at lags 1-12. Also, the error correction term $ZRPB_{t-1}$ in the retail price equation is given by:

$$ZRPB_{t-1} = RPB_{t-1} - 0.068\ RPP_{t-1} + 0.066\ INC_{t-1}.$$

a/ The squared simple correlations between actual and simulated one-step-ahead predictions of retail and farm beef prices (in levels), the (actual) farm-retail price spread, and commercial beef production are 0.982, 0.922, 0.679, and 0.764, respectively.

Table 3. Key Short-Run Elasticities and Flexibilities.

Equation	Variable	Elasticity/ Flexibility
Retail Demand:	QB_t	−0.078
	RPP_t	0.087
	INC_t	0.130
Farm-Retail Margin:	σ_{1t}	0.088
	QB_t	0.123
	PE_t	0.179
	WR_t	0.355
Commercial Production:	FPB_t	−0.304
	$\sqrt{h_{22t}}$	0.014
	PCO_t	0.064
	OFD_{t-1}	0.098

Note: All elasticities and flexibilities are evaluated at the sample means.

Table 4. Diagnostic Tests for the Estimated Multivariate GARCH-M Model.

Statistic		RPB_t	MRG_t	QB_t
Residual Skewness and Kurtosis:				
m_3		0.187	-0.238	0.237
m_4		3.196	2.872	3.654
Residual Q and Q^2 Statistics:				
Q(24)		44.156	29.930	43.216
$Q^2(24)$	RPB	39.370	–	–
	MRG	30.056	22.809	–
	QB	22.916	20.059	22.042
T-Statistics for Pagan -Sabau Consistency Tests:				
	RPB_t	1.016 (0.311)	–	–
	MRG_t	0.050 (0.960)	0.488 (0.626)	–
	QB_t	0.187 (0.852)	0.874 (0.383)	0.841 (0.401)

Note: The statistics m_3 and m_4 denote the standardized residual skewness and kurtosis. Q(24) and $Q^2(24)$ denote Box-Pierce statistics for 24th-order serial correlation in the standardized residuals and squared standardized residuals, respectively. T-statistics for Pagan-Sabau consistency tests were obtained using White's correction for heteroskedasticity. Asymptotic p-values are in parentheses.

Table 5. Average Monthly Simulated Market Equilibrium Impacts of Risk on the Beef Market by Year, 1971-89.

Year	RPB_t			FPB_t			QB_t		
	Actual	Siml.	Percent	Actual	Siml.	Percent	Actual	Siml.	Percent
1971	87.51	87.20	-0.36	58.26	59.59	2.27	1808	1803	-0.21
1972	93.06	93.10	0.06	60.62	64.12	5.92	1852	1783	-3.61
1973	104.94	103.62	-1.25	71.23	74.57	5.13	1757	1758	0.25
1974	97.47	97.71	0.30	62.23	68.52	10.58	1904	1872	-1.55
1975	94.27	93.45	-0.85	61.55	64.19	4.64	1973	1874	-4.85
1976	85.43	86.54	1.27	49.56	56.54	14.16	2139	2011	-5.91
1977	80.27	80.50	0.30	47.31	50.46	6.78	2082	2048	-1.60
1978	91.36	90.35	-1.10	57.08	59.94	5.04	2001	1935	-3.27
1979	102.31	101.29	-0.97	65.19	68.86	5.74	1772	1722	-2.57
1980	94.61	94.44	-0.19	59.00	61.41	4.13	1789	1730	-3.19
1981	86.13	86.45	0.36	51.10	53.85	5.44	1855	1812	-2.29
1982	82.41	82.63	0.29	48.82	50.88	4.37	1864	1829	-1.78
1983	78.42	78.81	0.51	45.86	48.33	5.47	1922	1899	-1.07
1984	75.63	75.71	0.10	45.24	46.60	3.05	1952	1939	-0.59
1985	70.92	71.34	0.58	39.54	42.45	7.60	1963	1977	0.84
1986	69.02	69.47	0.66	38.03	41.58	9.43	2018	1966	-2.41
1987	69.98	69.99	0.02	40.72	42.29	3.92	1950	1948	-0.05
1988	70.61	70.44	-0.24	41.82	43.46	3.96	1952	1940	-0.59
1989	71.49	71.18	-0.43	42.41	44.30	4.55	1915	1926	0.64
Avg.	84.52	84.43	-0.05	51.87	54.84	5.90	1919	1883	-1.78

Note: Percent denotes the average percentage increase (decrease) in the simulated value relative to the respective observed value.

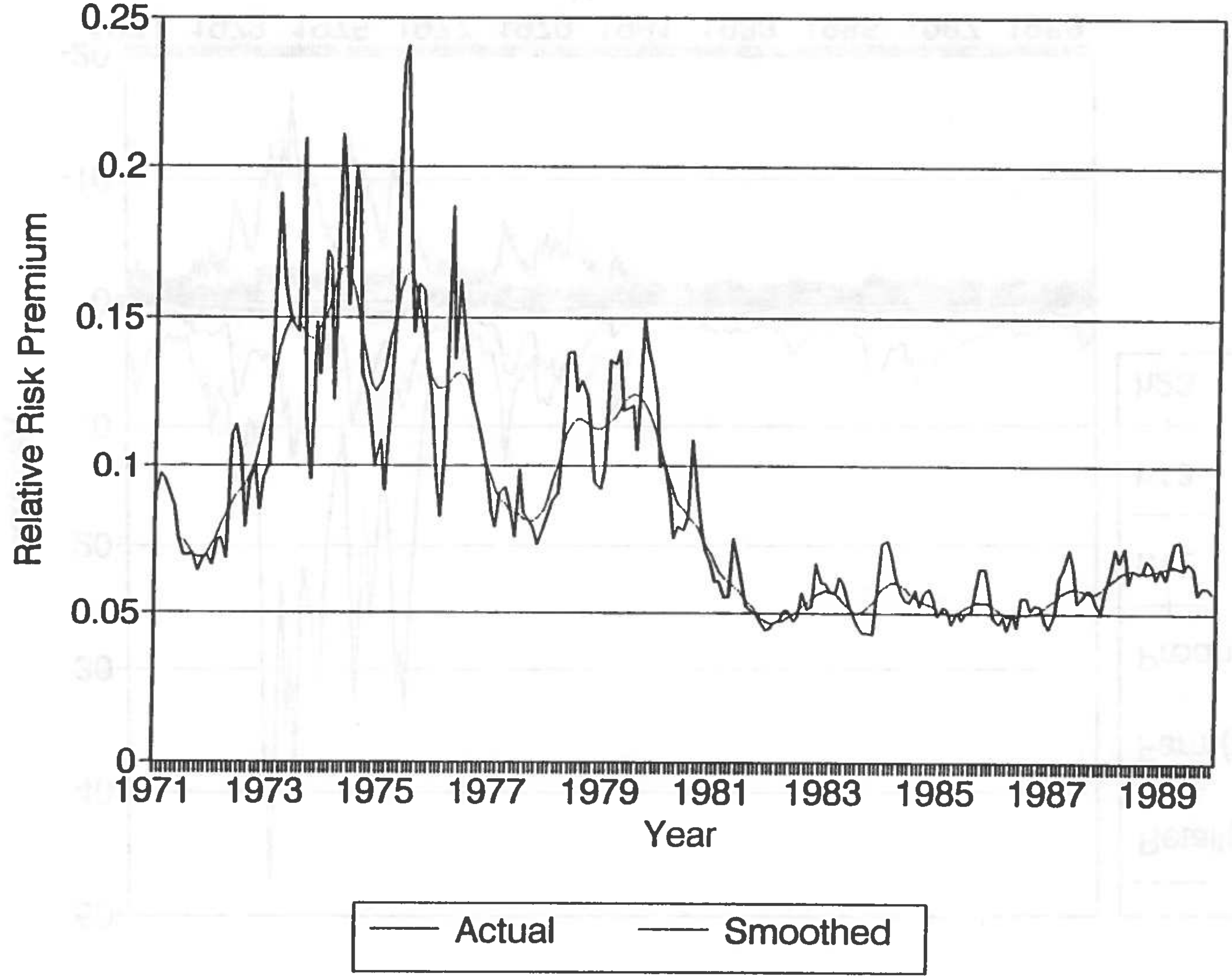

Figure 2. Time-varying relative risk premium in the expected farm-retail margin

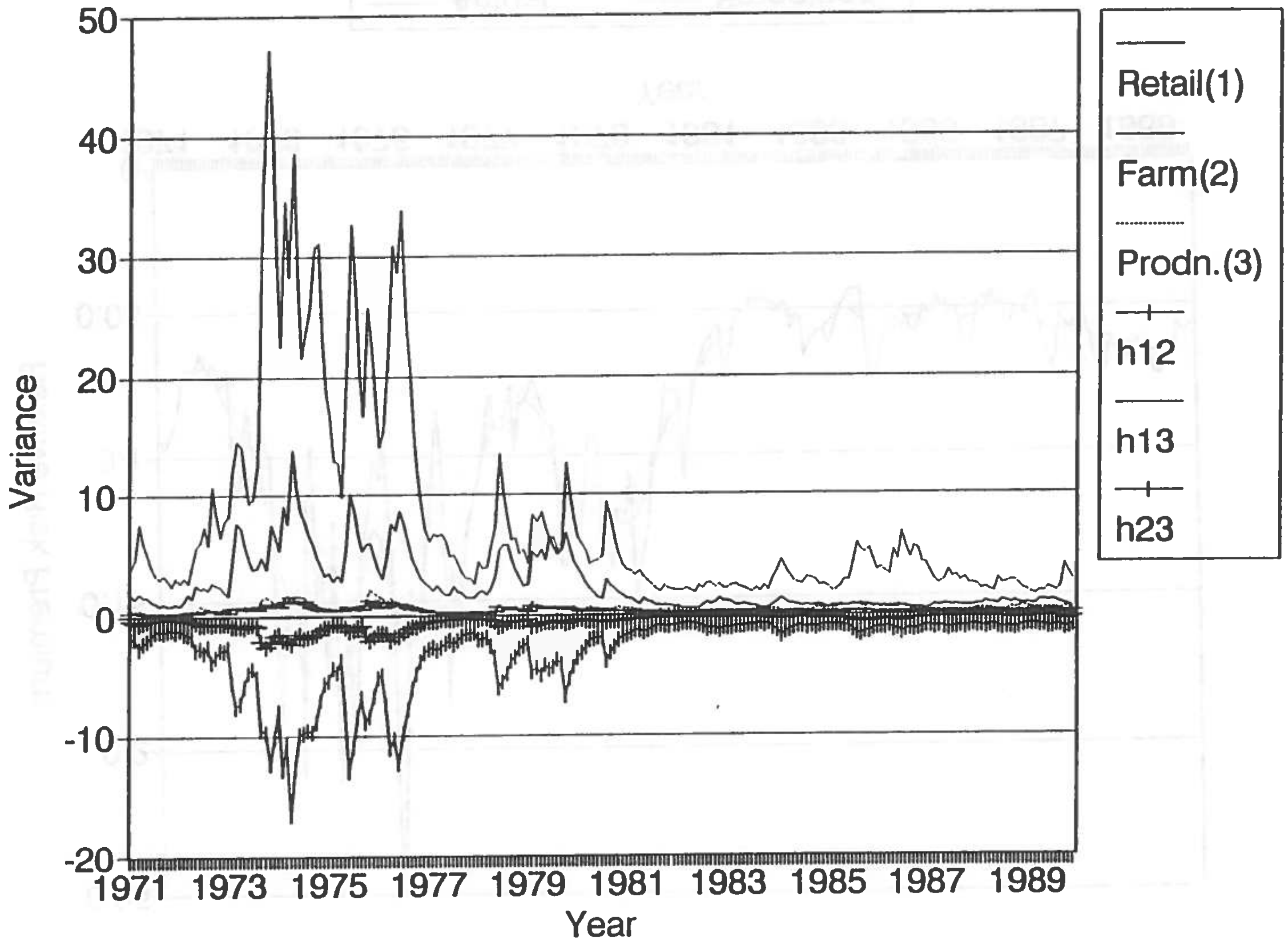

Figure 1. Time-varying conditional variance structure of the estimated GARCH-M model, 1971-89

Draft: Not for Quotation

Production Uncertainty and Profits

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Production Uncertainty and Profits

The use of profit functions in economic research is widespread (e.g. Lau, Shumway, Lopez). Profit functions provide a convenient way to obtain a coherent input demand and output supply system. They are conveniently used to measure welfare, economies of scale, substitution relationships, technical change and other conceptual measures of interest (e.g., Ball and Chambers, Chambers).

However, agricultural economists have recognized the need for a profit function approach that is more robust in the presence of risk. Some work has progressed to develop nearly general indirect expected utility functions under output price uncertainty (Chavas and Pope; Coyle). Although mechanisms exist to mitigate price uncertainty (forward and futures markets), production risk is usually substantial. Even in the presence of available crop insurance, non-indemnified production uncertainty is often large. Yet, dual methods to deal with production uncertainty have received scant attention (e.g. Daughety; Pope and Just).

The purpose of this paper is to develop a profit function approach that is consistent with expected utility, i.e., implicitly incorporates risk aversion. Stochastic technology follows the Just-Pope representation. It is location/scale flexible and thus has a relatively simple and convenient characterization of expected utility. The approach can be extended to higher order flexibilities but at the cost of increased notational and analytical complexity.

Under the Just-Pope characterization of production uncertainty, a simple expected profit function consistent with any arbitrary risk averse utility function is shown to exist. Then the properties, structure, and welfare consequences of this expected profit function are discussed. Finally, empirical possibilities for a leading case are examined.

II. Assumptions and Basic Model

Let expected utility be defined by

$$(1) \qquad E[U\{W_o + p\,[f(x) + h(x)\,\epsilon] - wx\}] \equiv E[U(W)]$$

where E is the expectation operator, U is utility, W_o is initial wealth, p is the nonrandom output price, x represents and N vector of inputs with corresponding prices w, ϵ is a random production disturbance with zero mean and variance one, $y = f(x) + h(x)\,\epsilon$, is output, and W is terminal wealth. Single-product production is maintained, and EU is assumed to be twice differentiable and concave in x with an an interior optimum. Fixed inputs are notationally suppressed and h is assumed monotonic in x.

First order conditions in vector form are

$$(2) \qquad E[U'(W)\,W_x]=0$$

where $U'(W)$ is the marginal utility of wealth, and W_x is the marginal contribution of inputs to wealth. The first order conditions in (2) can be rewritten as

$$(3) \qquad E(\pi_x) + p\ h_x\ \frac{E(U'\epsilon)}{E(U')} = 0$$

where $E(\pi_x) \equiv pf_x\text{-}w$ and subscripts denote derivatives. By rewriting expected utility as $U[W_o + E(\pi) - R] = E[U(W)]$, where R is the risk premium, (3) can be expressed as

$$(4) \qquad E(\pi_x) - R_x = 0$$

where profit is $\pi = p[f(x) + h(x)\epsilon] - wx$ and $R_x = -ph_x\,E(U'\epsilon)/E(U')$ is the marginal risk premium.

III. Expected Profit Maximization

The purpose of this section is to develop a conditional expected profit approach. As is intuitively clear from (4) and demonstrated in this section, maximizing expected utility in (1) is consistent with

$$(5) \qquad \max_x \ [E(\pi) \mid v \geq h(x)] = \bar{\pi}(p,w,v)$$

where $E(\pi_{xx})$ is negative definite subject to the constraint. That is, expected profit is maximized subject to h(x). Holding h(x) fixed equivalently constrains the variance, $E[h^2(x)\ \epsilon^2]$.

In order to define consistency, let $x^*(W_0, p, w)$ be the expected utility maximizing input levels corresponding to (1). Let $\bar{x}(p, w, v)$ be the conditional demands associated with (5). Consistency occurs when $x^*(W_0, p, w) = \bar{x}(p, w, v^*)$, where v^* is the utility maximizing level of v, $h(x^*)$.

Consistency thus requires that utility can be achieved by solving a two stage process with[1]

$$\text{Stage 1:} \quad \max_x \ [E(\pi) \mid v \geq h(x)] = \bar{\pi}(p,w,v)$$

$$\text{Stage 2:} \quad \max_v \ EU[W_0 + \bar{\pi}(p,w,v) + pv\epsilon]$$

First order conditions for Stage 1 are

$$(6) \qquad E[\pi_x(x)] - \lambda\, h_x = 0, \qquad v \geq h(x),$$

where λ is the Lagrangian multiplier. Second order conditions are assumed to hold for interior optimum $\bar{x}(p, w, v)$ and $\lambda(p, w, v)$. Typical of such sufficient conditions are that - h(x) is quasi-concave and $E(\pi)$ is quasi-concave (Arrow and Enthoven). The first order condition for Stage 2 is

$$(7) \qquad E[U'(W)(\bar{\pi}_v + p\epsilon)] = 0,$$

or

$$\bar{\pi}_v + pE(U'\epsilon)/E(U') = 0.$$

Second order conditions hold under risk aversion if $\bar{\pi}_{vv} < 0$[2]. Thus, the marginal contribution of v to $\bar{\pi}$ is balanced with the marginal contribution of v to the risk premium. Obviously, (7) is only consistent with expected utility maximization [(3) or (4)] if $\bar{\pi}_v = E(\pi_{xj})/h_{xj}$, j = 1,..., n. From (6), this is exactly the case. The Lagrangian multiplier at the optimum is the marginal effect of v on maximum expected profit, $\bar{\pi}_v$, and is equal to $E(\pi_{xi})/h_{xi}$, i = 1,...,n, establishing consistency.

Figure 1 depicts the solution to (5) while Figure 2 depicts the Stage 2 solution which is only indirectly of interest here. The next section focuses on the properties of the solution depicted in Figure 1 and its usefulness for a dual approach to production under uncertainty.

IV. Some Properties of Expected Profit

Under certainty or risk neutrality and the usual regularity conditions on technology, the expected profit function, π^*, is

i. decreasing in input prices such that

(8) $$\pi^*_w = -x^*(p, w),$$

ii. increasing in output price such that

(9) $$\pi^*_p = y^*(p, w),$$

iii. positively homogeneous in w and p,

(10) $$\pi^*(tp, tw) = t\,\pi^*(p, w),\ t>0,$$

iv. and convex in p and w implying positive semidefiniteness of

$$\begin{bmatrix} \pi^*_{ww} & \pi^*_{wp} \\ \pi^*_{pw} & \pi^*_{pp} \end{bmatrix}.$$

Equations (8) and (9) permit simple derivation of a coherent input demand and output supply system given a form for π^*. Equation (10) facilitates reduction of the number of

Figure 1
Expected Profit Maximization

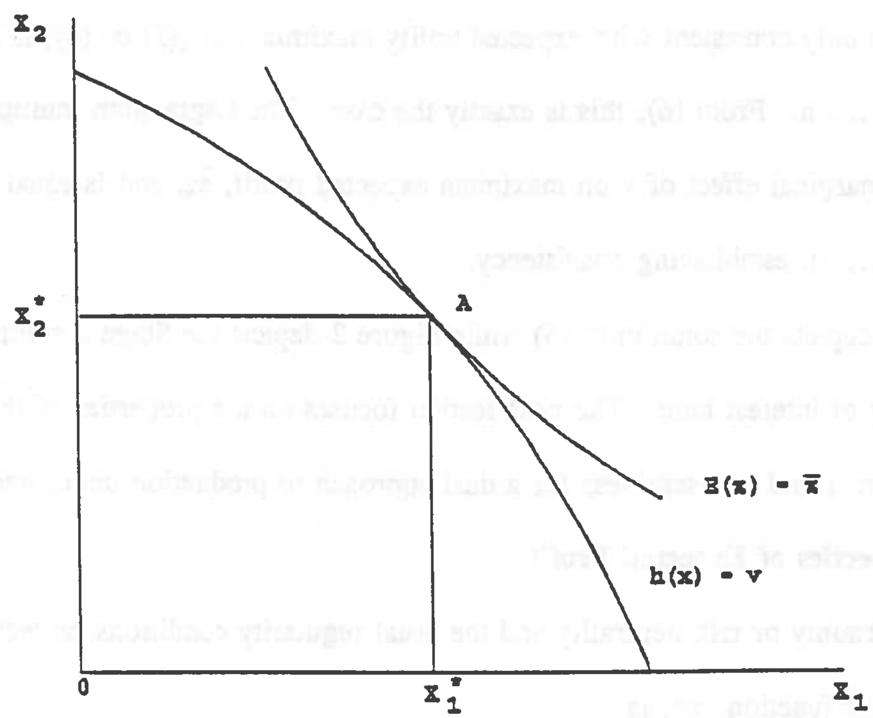
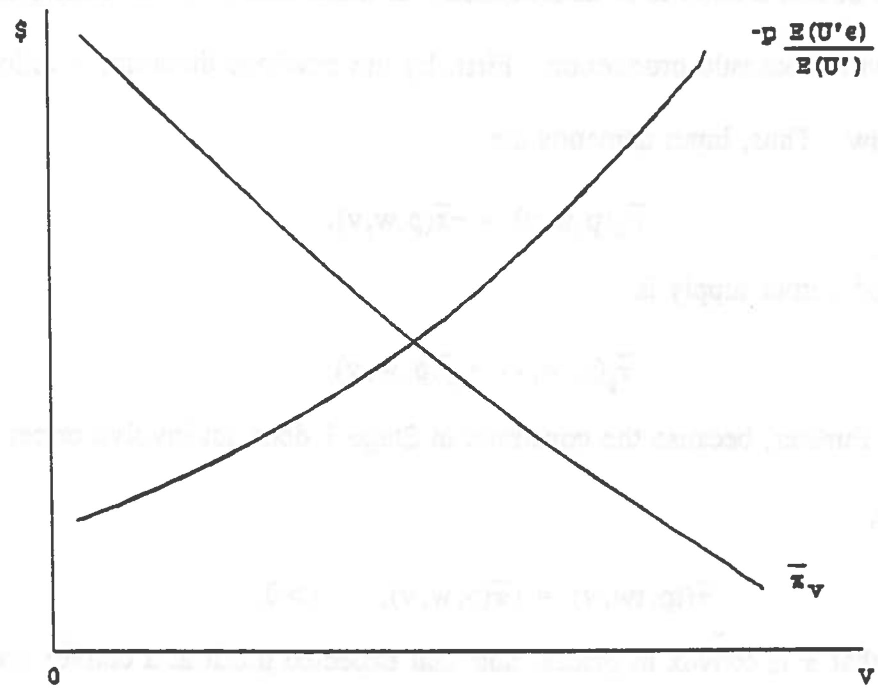


Figure 2
Expected Utility Maximizing Variance



econometric parameters to estimate.

The object of this section is to demonstrate that these conveniences extend to the case of risk aversion with stochastic production. First, by the envelope theorem, it follows that $\partial\bar{\pi}/\partial w = \partial E(\pi)/\partial w$. Thus, input demands are

$$(8') \qquad \bar{\pi}_w(p,w,v) = -\bar{x}(p,w,v).$$

Similarly, expected output supply is

$$(9') \qquad \bar{\pi}_p(p,w,v) = \bar{y}(p,w,v)$$

where $\bar{y} = f(\bar{x})$. Further, because the constraint in Stage 1 does not involve prices and $E(\pi)$ is linear in prices,

$$(10') \qquad \bar{\pi}(tp,tw,v) = t\bar{\pi}(p,w,v), \qquad t>0.$$

Finally, to show that $\bar{\pi}$ is convex in prices, note that expected profit at a convex combination of prices is lower than the convex combination of expected profits.

The only general new property to consider is the sign of $\bar{\pi}_v$. From (5) and Figure 1, it is clear that

$$(12) \qquad \bar{\pi}_v(p,w,v) \geq 0$$

yielding the usual mean-variance trade-off where the strict inequality holds at an interior optimum. The impact of characteristics (8')-(12) is that certainty procedures can be used to obtain demands and supplies from the expected profit function.

Next, the structure of π is considered under a few structural characteristics of f(x) and h(x). First consider the case of homotheticity of f(x) and h(x).

Homotheticity

Unfortunately, homotheticity does not delineate the structure of π as it does under certainty for profit or cost. The reason is that the slope of profit contours is altered by scale. The slope of an expected profit contour $E(\pi)$ in x for N=2 is

$$\frac{dx_2}{dx_1} = \frac{-\bar{\pi}_1}{\bar{\pi}_2} = \frac{-(pf_{x_1}-w_1)}{pf_{x_2}-w_2}. \tag{13}$$

Under homotheticity of h, changing v to v′ in Figure 3 will not alter the slope of h along a ray from the origin because

$$\frac{dx_2}{dx_1} = \frac{-h_{x_1}}{h_{x_2}}$$

and, under homotheticity, ratios of partial derivatives (marginal rates of substitution) are invariant to scale (Lau). However, homotheticity of f(x) implies that f_{x1}/f_{x2} is invariant to scale. This does not imply in (13) that $-\bar{\pi}_1/\bar{\pi}_2$ is invariant to scale. Thus, as v changes to v′ in Figure 3, equilibrium might move from A to B.

In the Appendix, it is shown under homotheticity of f and h that π is of the form

$$\bar{\pi}(p, w, v) = p\, F[\tilde{f}(z^*)\, H^{-1}(v)] - wz^*H^{-1}(v) \tag{14}$$

where $h(x) = H[\tilde{h}(x)]$, $f(x) = F[\tilde{f}(x)]$; $F', H' > 0$, and $\tilde{f}$ and $\tilde{h}$ are linearly homogeneous, and z* depends generally on p, w, and $H^{-1}(v)$. Hence, a somewhat specific form for $\bar{\pi}$ is obtained.

However, there are two leading case where $\bar{\pi}$ has a particularly convenient structure. First consider the case where $h(x) = f(x)$. This is the common multiplicative error specification. In this case, $\tilde{f}(z) = 1$, and $F(v) = H^{-1}(v)$. Hence (14) reduces to:

$$\bar{\pi} = pv - H^{-1}(v)\ \xi(w) \tag{14'}$$

where $\xi(w)$ is the cost of producing one unit of f(x) or expected output.

Another simple case arises when f exhibits constant returns to scale and h is homothetic. In the Appendix, it is shown in this case that

$$\bar{\pi}(p, w, v) = H^{-1}(v)\, \eta(p, w) \tag{15}$$

where η (p, w) = $p\bar{f}(z^*)$ - wz^* and z^* is homogeneous of degree zero in p and w and does not depend on v. In the case of (15), (8′) implies that input ratios are independent of v and the variance of production. This would be typified by the movement from A to C in Figure 3 and is analogous to the case of homothetic production under certainty.

Returns to Risk

Cost theory under certainty provides a simple measure of returns to scale given by the elasticity of cost with respect to output (e.g. Varian). In the same spirit, a natural definition of the returns to risk is the elasticity of expected profit with respect to risk,

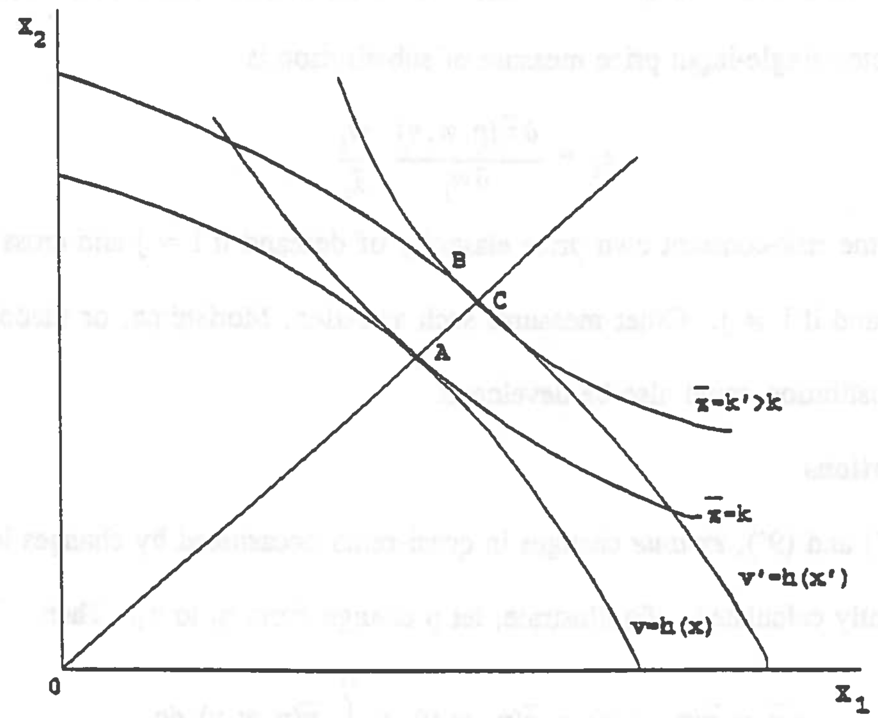
$$\epsilon_v = \frac{\bar{\pi}_v\, v}{\bar{\pi}}. \tag{16}$$

Thus, given a form and estimated parameters for $\bar{\pi}$, ϵ_v can be simply calculated. *A priori*, homotheticity does not yield an appreciably simpler calculation. However, if f exhibits constant returns to scale and h is homothetic as in (15) and v = H[h(x)], then

$$\epsilon_v = \frac{v}{H^{-1}(v)}\,\frac{\partial H^{-1}(v)}{\partial v}. \tag{16′}$$

To illustrate, if $h(x) = \prod_{j=1}^{n} x_j^{\alpha_j}$ and $\alpha = \sum_{j=1}^{n} \alpha_j$, then h(x) can be written as $h(x) = \prod_{j=1}^{n} x_j^{(\alpha_j/\alpha)\alpha}$. Therefore, $H^{-1}(v) = v^{1/\alpha}$ and $\bar{h}(x) = \prod_{j=1}^{n} x_j^{\alpha_j/\alpha}$. Hence, $\epsilon_v = 1/\alpha$. Thus, the reciprocal of the degree of homogeneity of h is the elasticity. If α is .5, then a one percent increase in the standard deviation of output given x would lead to a two percent

Figure 3



increase in expected profit.

Risk Constant Substitution or Response

A variety of measures of the ease of input substitution exist under certainty. In this case, a single-factor/single-input price measure of substitution is

$$\epsilon_{ij} = \frac{\partial \bar{x}_i(p,w,v)}{\partial w_j} \frac{w_j}{\bar{x}_i}$$

which measures the risk-constant own price elasticity of demand if i = j and cross price elasticity of demand if i ≠ j. Other measures such as Allen, Morishima, or shadow elasticities of substitution could also be developed.

Welfare Calculations

Given (8′) and (9′), *ex ante* changes in quasi-rents occasioned by changes in w and p can be conveniently calculated. To illustrate, let p change from p_1 to p_2. Then,

$$\Delta\bar{\pi} = \bar{\pi}(p_2,w,v) - \bar{\pi}(p_1,w,v) = \int_{p_1}^{p_2} \bar{y}(p,w,v)\, dp \ .$$

Thus, the area above the expected supply curve measures the welfare change. Similarly, the area under a derived demand curve easily measures the welfare effects of changes in an input price (the *ex ante* willingness to pay associated with compensating or equivalent variation).

Perhaps the more interesting case involves changes in risk, v. Letting p_L be the output price where $\bar{y}(p_L, w, v) = 0$, and p_H be the output price such that $\bar{y}(p_H, w, v') = 0$. Then, $\bar{\pi}$ at $\bar{y} = 0$ is fixed cost (not explicitly represented) and the welfare effect of a change from v to v′ at price p is

$$\Delta\bar{\pi} = \int_{p_H}^{p} \bar{y}(p,w,v')\, dp - \int_{p_L}^{p} \bar{y}(p,w,v)\, dp.$$

A similar calculation can be used for an essential input where production is driven to zero as an input price changes (Pope, Chavas and Just; Just, Hueth, and Schmitz). However, the more direct and empirically precise approach facilitated by the results here is to use the marginal effect of v on $\bar{\pi}$. Thus, $\Delta\bar{\pi} = \int_{v}^{v'} \bar{\pi}_v dv$ measures the changes in expected quasi-rents as the standard deviation of production is changed. In particular, the contrast between any v and risk neutrality, $\bar{\pi}(p, w, v) - \bar{\pi}(p, w, 0)$, is the risk premium or welfare effect of risk.

Efficiency

A common use of profit functions is to test for the efficiency of a producer or a set of producers (e.g., Lau). Under risk aversion, efficiency calculations must hold the variances of producers equal. A producer or set of producers can efficiently obtain a higher expected profit at constant prices by increasing production variance. Thus, $\bar{\pi}_1(p, w, v') > \bar{\pi}_2(p, w, v)$ for $v' > v$ does not imply that producer 1 is more efficient. It may only imply that producer 1 is less risk averse than producer 2. However, it is appropriate to conclude that producer 1 is more efficient if expected profit for firm 1 is higher than that of firm 2 at given prices and variance, when technologies are the same. A simple but effective measure of efficiency is

$$I = \frac{\bar{\pi}(p, w, v)}{p\ f(x)\ -\ w'x},$$

where $\bar{\pi}$ represents efficient expected profit and the denominator represents actual expected profit.

V. Estimation of $\bar{\pi}$

Estimation of profit and cost functions using dual methods under certainty is common. In the case of a cost function, C(y, w), the specification of a functional form yields estimable demands via Shephard's Lemma because output is observable.

In the case of stochastic production, however, expected output, upon which production cost more naturally depends, is not directly observable. Thus, estimation of $C(\bar{y}, w)$ is not straightforward. In addition, the estimation of $\bar{\pi}(p, w, v)$ is complicated because v is not directly observable.

The functional form of $\bar{\pi}$ depends on the specifications of both f(x) and h(x). It would be convenient if one could estimate v for an arbitrary $\bar{\pi}$; however, once a form of h(x) is specified, it directly affects the form of $\bar{\pi}$. Alternatively, suppose that $\bar{\pi}$ is specified as a translog function of p, w, and v. Because v is unobservable, it would be tempting to predict v by a low order polynomial in x. However, the low order polynomial, v = h(x), is likely logically inconsistent with a translog $\bar{\pi}$. For example, there may be no quasi-concave f(x) coupled with a quadratic h(x) that yields a translog $\bar{\pi}$. One possible logically consistent approach is to use flexible nonparametric techniques to predict v or $\hat{v}$ for a given form of $\bar{\pi}$. Then, (8') and (9') could be used to estimate $\bar{\pi}$(p, w,). To illustrate, Kernel or series estimators can be used to estimate v from the input choices x. One possibility is to estimate σ_y^2 and then regress these estimates on a large order polynomial in x (Gallant). This regression produces $\hat{\sigma}_y^2$ and taking the square root gives estimates $\hat{v}$ of v.

Next one must specify a form for $\bar{\pi}$ satisfying (8') - (12). Forms commonly used for the nonstochastic or risk-neutral case suffice, e.g., the normalized quadratic, translog, generalized Leontief, or any of McFadden's generalized linear forms. Asymptotically, regressions based upon $\bar{\pi}(p, w, \hat{v})$ created in this manner will be consistent when the error in creating $\hat{v}$ is uncorrelated with (p, w). The most unsettling aspect of this procedure is that low order polynomials are typically used for v in which case there are clear implications for the form of $\bar{\pi}$ as above. This problem is also encountered in using other orthogonal predictors of v such as instrumental variable forecasts based on lagged values of p and w.

Another approach is to derive the value of v exactly from $\bar{\pi}$ using duality. This is the approach used by Pope and Just in the estimation of a cost function which depends on $\bar{y}$. To illustrate this approach to the estimation of an expected profit function, assume

$\bar{\pi} = K(v)\, \eta(w, p)$, $K' > 0$ as in (15) under homotheticity of h and linear homogeneity of f. From (10') $\bar{\pi}$ and thus η is linearly-homogeneous in w and p.

Normalizing profit by p, $\hat{\pi} \equiv \bar{\pi}/p = K(v)\, \eta(w/p, 1)$. Now let η take the Generalized Leontief form,

$$\hat{\pi} = -K(v)\, [\alpha_0 + \sum_j B_{0j} r_j + \sum_i \sum_j B_{ij} r_i^{1/2} r_j^{1/2}], \qquad B_{ij} = B_{ji}, \qquad i,j=1,\ldots,n.$$

where $r = w/p$. By definition,

$$\hat{\pi} \geq \bar{y} - rx$$

for a given x and arbitrary positive r. By Theorem 2 of Epstein, under appropriate regularity conditions, v(x) can be recovered as the solution to the problem

$$\underset{r>0}{\mathrm{Max}} \quad \frac{1}{K(v)} = -\frac{\alpha_0 + \sum_j B_{0j} r_j + \sum_i \sum_j B_{ij} r_i^{1/2} r_j^{1/2}}{\bar{y} - \sum_j r_j x_j}$$

where, expected profit $\bar{y} - \sum_i r_i x_i$ is assumed positive. This maximization problem can be solved (see the Appendix) to find that $1/K(v) \equiv \mu$ where μ is the minimum root of the matrix

$$D = [\hat{X}\, B_0\, \hat{X} + \hat{X}\, B\, \hat{X}],$$

where $\hat{X}$ and $\hat{B}_0$ are diagonal matrices defined in the Appendix. Hence, $K(v) = 1/\mu$, so that demand responses in (8′) are

$$\bar{x}_i = \frac{1}{\mu}[B_{0i} + \sum_{j=1}^{n} B_{ij} (r_j/r_i)^{1/2}], \qquad i=1,\ldots,n.$$

This provides a readily estimable almost linear system of demand responses.

The envelope theorem in (9′) implies that expected supply can be obtained from directly from expected profit as $\bar{\pi}_p = \bar{y}$. Thus, actual supply can be obtained from

$$y = \bar{\pi}_p + p\ h(x)\ \varepsilon$$

Thus, it is possible to use actual output in a nonlinear regression to estimate parameters of a supply function if $h(x) = H(1/\mu)$ is known. The essential point is that the actual supply function depends on w, p, and v and a heteroskedastic error. Because H is seldom known, a more straightforward approach uses (10′) and estimates mean supply as $\bar{y} = -\bar{\pi}_w r$.

Finally, we note that there is nothing preventing estimation of the second stage along with the first stage estimation. However, the second stage must explicitly consider a specification of utility [see (7)]. This is not econometrically difficult especially if the empirical probability distribution is used. Presumably, if one specifies the utility function correctly, then system estimates using the entire covariance matrix derived from both first and second stage estimates are more efficient. However, misspecification of the second stage will contaminate parameter estimates.

VI. Conclusions

Generalization of the theory of expected profit maximization under Just-Pope type production uncertainty has led to a theoretically worthwhile and empirically tractable analysis. A remaining restrictive assumption is output price certainty. There are two approaches to including output price uncertainty. First, with hedging, it can be shown that the profit function approach is consistent with expected utility maximization where output price is replaced by the futures price. Second, cost minimization can be used as the efficient first stage. Pope and Chavas have shown that cost minimization is a possible efficient first stage problem while Pope and Just have estimated a first stage Generalized Leontief cost function under production uncertainty.

Appendix

Homotheticity of h(x) and f(x)

Let $K(v) = \bar{h}(x)$, $H' > 0$ be the homothetic representation of the constraint $v = H[\bar{h}(x)]$, where h is positively linearly homogeneous and $K(v) = H^{-1}(v)$. The problem for the firm is

$$\operatorname*{Max}_{x}\ E[\pi(x,p,w)\,|\,K(v) \geq h(x)] = \bar{\pi}(p,w,v).$$

By homogeneity, the constraint can be written $1 = \bar{h}(z)$ where $z = x/K(v)$. Let f be homothetic as well where

$$f(x) = F[\bar{f}(x)], \quad F' > 0,$$

where $\bar{f}(x)$ is positively linearly homogeneous. Hence,

$$E(\pi) = p\,f(x) - wx = pF\,(K(v)\,\bar{f}(z)) - wzK(v)),$$

and

$$\operatorname*{Max}_{z}\ [E(\pi)\,|\,1 = \bar{h}(z)] = \bar{\pi}(p,w,v) = p\,F[H(v)\,\bar{f}(z*)] - wz*\,H(v)$$

where $z^* = z^*(p, w, v)$ at the optimum.

Note that when F is the identity mapping as under linear homogeneity of f(x), i.e., $\bar{f} = f$, then K(v) factors out and

$$\operatorname*{Max}_{z}\ [E(\pi)\,|\,1 = \bar{h}(z)] = \operatorname*{Max}_{z}\ [K(v)(p\bar{f}(z) - wz)\,|\,1 = \bar{h}(z)]$$

$$= K(v)\ \tilde{\pi}(p,w) \equiv \bar{\pi}(p,w,v)$$

where $\bar{\pi}$ and $\tilde{\pi}$ are positively linearly homogeneous in (p, w) and $\tilde{\pi}$ is the unit variance expected profit function.

The Generalized Leontief Expected Profit Function

Let $\hat{\pi}(v, w, p)/p = \hat{\pi}(v, r)$ where $r = w/p > 0$. Further, let

$$\hat{\pi} = -K(v)\,[\alpha_0 + \sum_j B_{0j} r_j + \sum_i \sum_j B_{ij} r_i^{1/2} r_j^{1/2}], \qquad B_{ij} = B_{ji}, \qquad i,j = 1,\ldots,n.$$

Then $\hat{\pi} \geq \pi = \bar{y} - r'x$ for feasible x, $\bar{y}$. Because K is monotonic in v, maximizing K(v) will establish the inequality analogous to Diewert (1971). Thus, the problem is

$$\underset{r>0}{\text{Max}}\ L = \frac{1}{K(v)} \leq \frac{-\left[\alpha_0 + \sum_j B_{0j} r_j + \sum_i \sum_j B_{ij} r_i^{1/2} r_j^{1/2}\right]}{\bar{y} - \sum_j r_j x_j}.$$

Let $r_j^{1/2} = t_j x_j^{-1/2}$, $j = 1,\ldots,n$. Then L can be written as

$$L = \frac{-\left[\alpha_0 + \sum_j B_{0j} t_j^2 x_j^{-1} + \sum_i \sum_j B_{ij} t_i t_j x_i^{-1/2} x_j^{-1/2}\right]}{\bar{y} - \sum_i t_i^2}.$$

Maximizing L in t is equivalent to maximizing L in r. Note that L can be written in matrix form as

$$L = \frac{-\left[\alpha_0 + t'\hat{B}_0 \hat{x}\hat{x} t + t'\hat{x} B \hat{x} t\right]}{\bar{y} - t't}$$

where

$$\hat{x} = \begin{bmatrix} x_1^{-1/2} & & 0 \\ & \ddots & \\ 0 & & x_N^{-1/2} \end{bmatrix}, \text{ and } \hat{B}_0 = \begin{bmatrix} B_1 & & 0 \\ & \ddots & \\ 0 & & B_N \end{bmatrix}.$$

Optimizing with respect to t obtains $L_t = 0$ which yields

$$(\bar{y} - t't)\left[\hat{B}_0(\hat{x}\hat{x})2t + 2\hat{x}B\hat{x}t\right] + \left[\alpha_0 + t'\,\hat{B}_0(\hat{x}\hat{x})t + t'\hat{x}B\hat{x}t\right]2t = 0.$$

This condition is satisfied if,

$$\text{(A.1)} \qquad -\left[(\hat{B}_0(\hat{x}\hat{x}) + \hat{x}B\hat{x})t - Lt\right] = 0.$$

Hence, L is maximized by finding a stationary value of L which is the minimal root of the matrix $D = [\hat{B}_0(\hat{x}\hat{x}) + \hat{x}B\hat{x}]$. Let μ be this root, $K(v) = 1/\mu$. Then, the system of demand equations is

$$\text{(A.2)} \qquad -\bar{x}_i = -\frac{1}{\mu}\left[B_{0i} + \sum_j B_{ij}(r_j^{1/2}/r_i^{-1/2})\right], \qquad i=1,\ldots,n.$$

To consider whether second order conditions are satisfied at (A.1), not that the Hessian at the optimal t is

$$\text{(A.3)} \qquad -\left[(B_0(\hat{x}\hat{x}) + \hat{x}B\hat{x}) - LI\right].$$

Given the convexity of π^* in r, $-[B_0\,\hat{x}\hat{x} + \hat{x}B\hat{x}]$ must be positive definite. However, the positivity of L implies that LI is also positive definite. Thus, positive definiteness is assured if the parameters matrices $\hat{B}_0$ and B imply that L is convex in t.

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Footnotes

1. The second stage second order condition is $EU'(W)\ \bar{\pi}_{vv} + EU''(W)\ (\bar{\pi}_v + p\epsilon)^2$. Hence, $\bar{\pi}_{vv} < 0$ and risk aversion is sufficient.

2. The dual to this problem is to minimize v(x) subject to $E(\pi)$ fixed. These are classically dual-problems as portrayed in Epstein. The approach taken here could be extended to revenue functions and indirect production functions.

MODELING IRRIGATION DECISION AND STREAM FLOW MINIMUMS--AN APPLICATION OF DISCRETE STOCHASTIC PROGRAMMING AND ZERO-ONE SAFETY FIRST PROGRAMMING

by

Glenn A. Helmers, Joseph A. Atwood, and Tariq Javed[1]

Introduction

Currently in southern and southwestern Nebraska there are major conflicts regarding uses for surface water. These conflicts have resulted in litigation, regulatory pressure, and requests for political action. Newspaper accounts of these conflicts have appeared almost daily during periods of high water usage. There are five groups or interests involved in the management of impounded surface water. These interests represent irrigation, recreation, power generation, flood protection, and stream flow protection. This paper focuses on irrigation. Irrigation has had a long history and been a prime reason for the impoundment of streams and rivers. Water use for irrigation peaks in mid summer. Where previously farmers could be assured of traditional water allocations, recently this has changed, and farmers now face uncertainty regarding water availability throughout the irrigation season. Therefore, they have to make planting decisions without knowing water availability during the growing season.

A second interest is recreation which includes boating, fishing, and associated service businesses. For this interest, stability of water levels in impoundments is important. Traditionally water levels in impoundments have varied to some degree, but in recent years large expanses of mud have become commonplace in some impoundments.

For some impoundment situations, power generation is an important interest in the management of water use. This activity is more efficient under stable water levels even though power generation varies depending upon demand, alternative sources of power, and peaking generation policy.

Flood prevention in this study area has recently become an almost forgotten reason for the development of impoundments. In the last decade water levels have fallen to historically low levels; therefore, flooding has not been a concern. Still, in the longer run this issue cannot be ignored because unless reservoir levels retain sufficient flood control capacity, major rain storms

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can result in major flood damage.

Finally, there is increasing interest in using impoundment releases to maintain stream flows. This general interest can be termed environmental even though environmental concerns also pervade other uses of impounded water. Here, maintaining stream flow is important to support fish and fowl populations as well as other environmentally derived benefits.

Clearly these competing interests make management decisions regarding surface water difficult. Not only is the intraseasonal management of water complex, but interseasonal management adds an additional complexity. For some of these interests--agriculture and power generation--the quantification of benefits of water availability by time period can be estimated. For other interests, economic quantification of costs or benefits of reduced water availability is difficult to assess. For these interests, attention is generally focused on absolute minimum or maximums in a more subjective sense. Here, stream flow levels are examined simultaneously with irrigation and both interests are quantified. Considerable interest exists for maintaining stream flows at particular minimum levels for environmental and other reasons. Obviously, such minimums can cause limitations on other uses of water (here irrigation) in low stream flow years. As minimum stream flows are increased it can be expected that optimum crop and irrigation strategies change.

It should be noted that while impoundments are an important aspect of the water environment, impoundment water release is not examined here. Rather, the context of the problem can be viewed as an impoundment which releases water at the rate water enters. Water release strategies can obviously modify the results of this analysis, but still other competing interests need to be considered in such an analysis.

The objective of this paper is to analyze the decision making process in crop selection and irrigation strategies under uncertain surface water supplies. As an additional constraint, probabilities of maintaining stream flow minimums are varied, the resultant impact on crop selection, abandonment, and irrigation strategies examined.

Specific Focus

This paper is directed at the impact of water availability on agricultural crop production. Rather than examining agriculture in a comprehensive model of competing interests, this analysis examines irrigated agriculture as a single decision component in the framework of uncertain intraseasonal water supplies along with probability constraints relating to maintaining particular levels of stream flows not usable by irrigation. By better understanding the dimensions of variable water supplies on agricultural decisions, the economic value of additional or reduced water availabilities can be quantified. Further, such a component later can be placed in comprehensive decision making processes.

The decision processes of crop selection and water use under uncertain water is thus basic to the process of complex and difficult water management decisions when there are competing interests. Previously, irrigation water allocations to agriculture allowed producers to supplement natural precipitation at levels to essentially eliminate crop stress while growing heavy water using crops such as corn. Uncertainty in these allocations requires a different decision process, however.

Historically, precipitation records provide quantifiable variability of one source of water for crop production. With impoundments, no quantifiable measure of intraseasonal irrigation water variability is available. This is because a) impoundments were managed so limitations have not occurred previously and b) future management decisions for impounded water are unclear. Again, for these reasons this analysis of crop selection and intraseasonal irrigation strategies is directed at variability of stream flows assuming no impoundment occurs. This essentially assumes that under impoundment, irrigation water is released at the same rate as it originates without concern to other competing uses.

Decision making under uncertain water supplies is considerably different from dryland crop production as well as irrigated crop production using groundwater. In these two situations, initial decisions are also made in the face of uncertainty. However, in dryland crop production subsequent decisions related to water management are extremely limited. In irrigated crop production using groundwater, uncertainties related to precipitation can be largely compensated by increased or decreased pumping. In these two situations the impact of variable precipitation on initial crop selection and (in the second case) succeeding irrigation strategy is far less complex than where irrigation supplies are subject to variability and insufficient to prevent crop stress. In this case, flexibility in reducing the use of irrigation water is more important. Thus, if water supplies are highly variable, the initial crop selection mix and irrigation strategy tends to favor crop mixes which relatively perform better under reduced water.

The problem of determining an initial optimal crop mix and conditional irrigation strategies is well suited to dynamic decision making in which earlier decisions are conditioned by later possibilities. Hence, in this study the technique of Discrete Stochastic Programming is used to analyze the optimal decision process. In addition, constraints related to insuring the probability of maintaining particular levels of stream flows are incorporated into the discrete programming model through a zero-one integer safety first model.

General Procedure

A Discrete Stochastic Programming model was employed to determine initial crop choice and conditional irrigation decisions in a southern Nebraska setting. The model made an initial cropping choice and two irrigation level choices. Each irrigation choice was made during two stress periods (stages) (May-June and July-August) in which water allocations are assumed to be assigned to irrigation district managers.

Stream flows were secured from U.S. Geological data for the closest station to the study area. This was located immediately upstream from the reservoir. Data was available for 49 years. Precipitation data were also examined so irrigation response could be evaluated above available precipitation. Because of dimensionality concerns, the 49 years were partitioned into three states, high, medium, and low. For the two periods, these stream flows are 3575, 1696, and 1015 acre feet of water for Period 1 and 1804, 850, and 389 acre feet of water for Period 2. This is water available to the crop after distribution losses are considered. Equal probability was assumed for each state.

The basic choices to the firm are 1) which crops to plant among corn (Crop A), soybeans (Crop B), and grain sorghum (Crop C), 2) the conditional water level decisions for Stage 2 after the actual stream flow in Stage 1 is observed, and 3) the conditional water level decision to complete the crop year after the actual stream flow in Stage 2 is observed. Water decision choices related to whether the crop was maintained at a low (30 percent), medium (50 percent), or high (90 percent) stress level during the production stage. The model fully examined all branches not truncating any branches. That is, if in the first stage, an irrigation policy of using water to maintain only a high stress condition was selected, the opportunity of watering that crop during the second stage to maintain a low stress level was available if high stream flows were observed. Abandonment of acreage was allowed in the model, an alternative important to crop decision processes under high water variability.

The water response requirements to maintain constant stress levels were developed from EPIC (Erosion-Productivity Impact Calculator) Williams, et al. This provided a consistent estimate of water response for each of the three crops.

A two thousand acre "base" was used for cropland availability relative to the stream flows analyzed. An optimal linear programming strategy was secured for the "base" solution. Second, solutions were obtained from employing various probabilities of maintaining various target stream flow in the two time periods. This model aspect is presented in the next section.

Dryland production alternatives were not investigated in this model. Thus, three water levels were examined with the fourth being abandonment (no ending return).

Discrete Stochastic Programming

Following Cocks, Discrete Stochastic Programming (DSP) is a useful technique for decision making where the objective function, restraints, and input-output coefficients have discrete probability distributions. Beginning with the Linear Programming problem

(1) $\quad \text{Max } z = \underline{c}'\underline{x},$

(2) $\quad A\underline{x} \leq \underline{b},$

(3) $\quad \underline{x} \geq 0,$

where $A = (a_{ij})$ is an m X n matrix of constants, $\underline{b} = (b_i)$ is an m x 1 column vector of constants, $\underline{c} = (c_j)$ is an n x 1 column vector of constants, and $\underline{x} = (x_j)$ is a control vector to be determined.

The corresponding discrete stochastic linear programming problem can be formulated in a number of ways (under a number of sets of assumptions) having in common the introduction of the probability distribution.

(4) $\quad \text{Prob. } [(A, b, c) = (A_k, b_k, c_k)] = p_k \qquad (k = 1, 2, ..., k)$

(5) $\quad \sum_{k=1}^{k} p_k = 1.$

The control vector, $\underline{x}$, may now be contingent on the eventuating environment in some way

(6) $\quad x = x_k \mid (A, b, c) = (A, b, c)_k \qquad (k = 1, 2, ..., k)$

DSP is an appealing approach to the analysis of problems which are of sequential and stochastic nature. The optimum decision process evaluates subsequent activity paths in later stages with the optimal decisions for earlier stages dependent upon subsequent optimal decisions. Working backwards the process is useful for understanding an optimal initial choice and subsequent conditional choices. In addition, for financial analysis, DSP is a useful method of understanding impacts of financial penalties resulting from disasters. Still another manner in which DSP has been effectively used is by incorporating utility functions to functional (return) outcomes.

In this problem setting, DSP appears particularly useful in that the initial crop mix is important to (yet is influenced by) subsequent flexibility in watering decisions. For such problems, the greater the subsequent flexibility, the less flexibility is necessary in the initial crop choice. For example, soybeans function as a crop which after undergoing initial stress can compensate for earlier stress in later periods. This flexibility enables the initial crop mix to be less "safe" than if such flexibilities are absent.

DSP suffers from the "curse of dimensionality" because state paths and column paths "explode" when periods increase. Thus, pressures exist to limit probability states in such models. Here, three probability states are used.

Safety First Programming--A Zero-One Approach

Safety-first methods have been proposed as an approach to making decisions in a risky environment (see Roy, Kataoka, Telser, Roummasset). In general the methods to implement safety-first programming have required assumptions of tractable multivariate distributions (Pyle and Turnovsky) or the use of conservative stochastic inequalities (Telser, Sengupta, or Atwood). The methods presented in this paper allow safety-first modeling with finitely discrete multivariate populations or samples. The method uses exact probabilities or estimates of probabilities rather than the usually conservative probability bounds of the stochastic inequality methods presented by Atwood, or Atwood et al. The method is not without cost, however, in that a zero-one optimization algorithm is required.

Safety-First Criteria

Safety first models are constrained by the probability of failing to achieve certain goals of a decision maker. For the following discussion, an income goal is assumed, but in the analysis, stream flow minimum goals are used. The probability and goal of concern can be denoted as

$$(7) \qquad \Pr(z < g)$$

where Pr(*) denotes the probability of the event (*),

z denotes a random variable (usually income), and

g is a goal level for the income random variable.

Several forms of safety-first behavior have been defined and discussed. Roy proposed that decision makers choose the alternative which minimizes (7) or the $\Pr(z > g)$. Roy's criterion can be viewed as a special case of a Fishburn mean risk utility function. Fishburn proposed the following utility function

$$(8) \qquad U(z) = z - K(g-z)^{\alpha}\, I_{(-\infty,g)}(z)$$

In this expression, U(z) is a VonNeuman-Morgenstern utility function, K and α are parameters, and $I_{(-\infty, g)}(z)$ is an indicator function which multiplies by 1 if z < g and 0 if z > g. Given this utility function, expected utility is

(9) $E(U(z)) = E(z) - K\rho(\alpha,g)$

when E(*) is the expectation operator and $\rho(\alpha,g) = \int_{-\infty}^{g} (g-x)^{\alpha} f(x)dx$. When $\alpha = 0$, the expected utility equals D(z) - K Pr(Z < g). If K is very large, maximizing expected utility is essentially minimizing the probability of income falling below g, i.e. Roy's criterion. Although Roy's criterion can be viewed as an expected utility criterion, it is commonly referred to as a safety-first model. Telser suggested a lexicographic alternative in which expected income, μ_z is maximized while requiring that Pr(z < g) < δ where δ is an exogenously determined constraint on the probability of income falling below g. Kataoka suggested a lexicographic alternative in which decision makers attempt to maximize g, the level for which Pf(z < g) < δ.

Obtaining optimal solutions for the above criteria is usually difficult if mixtures of activities or investments are feasible. Let X_i denote the level of the ith activity in the portfolio with i = 1, 2, ... k, and let Z equal the aggregate income associated with the portfolio. Implementing safety-first criteria involves the selection of an activity mix which best satisfies the objective while the probability of aggregate income falling below g now involves multiple integrals. Numerically solving such problems is quite difficult with continuous multivariate distributions unless the distributions are especially tractable. However, if the multivariate distribution is finitely discrete, or can be approximated as such, exact solutions to the above criteria can be obtained by modifying results presented in Hillier and Lieberman.

A zero-one integer programming can be used to guarantee that no more than s of t constraints are nonbinding. Using similar procedures enable Fishburn's, Roy's, Telser's, or Kataoka's criteria to be implemented. Specifically Fishburn's model can be implemented by

(10) Maximizing $\underline{\mu}'\underline{x} - K\underline{r}'\underline{d}$

Subject to $A\underline{x} \leq \underline{b}'$

$C\underline{x} - \underline{1}g + M\underline{d} \geq 0$; and

$\underline{x} \geq \underline{0}$, $d_i = 0$ or 1   i = 1, 2, ... n, g fixed.

In expression (10), $\underline{\mu}'$ is a transposed kx1 vector with μ_i the expected income associated with activity j, $\underline{r}'$ is a transposed nx1 vector of probabilities with r_i the probability of realizing state i; $\underline{d}$ is an nx1 vector of zero-one variables; A is an mxk matrix of constraint coefficients; $\underline{x}$ is a kx1 vector of activity levels, C is an nxk matrix with C_{ij} the income generated by activity j if state i is realized; $\underline{1}$ is a vector of ones, g is the goal in expression (1), and M is a diagonal matrix with "large" values on the diagonal. In system (10), d_i will equal 1 only if aggregate income in state i falls below g. If K is set very large (or $\underline{\mu}'\underline{x}$ eliminated) system (4) models Roy's criterion.

Telser's criterion can be modeled similarly as:

$$\text{(11)}\quad \text{Maximize } \underline{\mu}'\underline{x}$$
$$\text{Subject to: } A\underline{x} \leq \underline{b};$$
$$C\underline{x} - \underline{1}g + M\underline{d} \geq \underline{0};$$
$$\underline{r}'\underline{d} \leq \rho; \text{ and}$$
$$\underline{x} \geq \underline{0},\ d_i = 0 \text{ or } 1 \quad i = 1, 2, \dots n, g \text{ fixed.}$$

In expression (11) ρ is an exogenous limit on the probability of aggregate income falling below g and the other parameters and variables are as previously defined. Kataoka's criterion can be expressed as

$$\text{(12)}\quad \text{Maximize } g$$
$$\text{Subject to: } A\underline{x} \leq \underline{b};$$
$$C\underline{x} - \underline{1}g + M\underline{d} \geq 0;$$
$$\underline{r}'\underline{d} \leq \rho; \text{ and}$$
$$\underline{x} \geq \underline{0},\ d_i = 0 \text{ or } 1 \quad i = 1, 2, \dots n.$$

Additional detail in terms of an income application can be found in Watts, et al. (1989).

Results

The results of the analysis are presented in Table 1 for the unconstrained discrete stochastic programming solution and the remaining tables for alternative probability levels for maintaining stream flow requirements.

The model size was 111 rows and 263 columns of which 12 columns were integers. States were partitioned (on basis of historical stream flow) into three for two period. There were three crops and initially selected and three stress levels (selected by irrigation level) for the remaining two periods each of these two following observed stream flows.

The richness of the model can be observed by forcing the DSP solution without stream flow constraints into a stream flow constraint context. This was done, for example, for a .3 probability level (in both periods) for a target stream flow of 500 acre feet in period 1 and 200 acre feet in Period 2. The objective function for the unconstrained solution is \$136,266. When initial crop choices of the unconstrained solution are forced in the above setting the objective function is \$83,338. However, the DSP result for the 500-200, .3-.3 (targets for Period 1 and 2 and probability levels permitted to exceed targets in each period respectively) is \$110,837. This is a considerable difference.

An even more dramatic example of using an unconstrained solution vs. a probability based-stream flow minimum solution is for a zero percent probability level where 300 acre feet are required as a minimum in both periods. When the initial crop choices from the unconstrained solution are forced into that context this results in an objective function of $-13,330 while the solution derived for that setting yields a return of $45,568. This indicates that the unconstrained solution can be a very poor choice and offers little conditional decision potential compared to a "designed" solution.

For probability levels of 1, this allows the target stream flow constraints to be violated 100 percent of the time (three violations here). This, regardless of target level, is the unconstrained DSP solution. A range of .667 to .999 probability level allows two of the three stream flows to be exceeded. A .334 to .666 probability allows only one right hand side stream flow to be violated. Finally a zero probability level allows no violation of the right hand sides. This, of course, is a totally constrained solution and results in rapidly declining objective functions as the targets approach the right hand side becoming infeasible when the target exceeds the most limiting right hand side for one or both of the two periods.

In Table 1 the unconstrained DSP solution is presented. One solution (Table 2) is shown where two stream flow violations are allowed. Two solutions (Table 3 and Table 4) are presented for the provision that only one stream flow violation is allowed. Identical stream flow targets are examined in Tables 3 and 4. Table 5 presents the solution in which no violation of stream flow minimums is allowed at the probability level of 30 percent while Table 6 presents the equivalent solution at zero percent probability level. The choice of target stream flow minimums in each period depends upon the desired analysis. Here, for Tables 1-6 equal minimums for each of the two periods or stages are examined.

The direct and conditional cropping decisions from each table are somewhat complex to trace. In Table 3, for example, the results should be read as follows: Six target remaining stream flows are presented, and they are equal for each period. The first (0-0) is the unconstrained solution. The probability of failing to meet each stream flow target is no greater than 60 percent which allows the targets to be exceeded 40 percent of the time. Of the six, two (400-400 and 500-500) exceed one right hand side constraint (389 in period 2). Examining, for example, the 400-400 solution, 1308 acres of soybeans (B) and 144 acres of grain sorghum (C) are initially selected. This requires idling 548 acres. This could be termed abandonment but is not noted as such in the table. The conditional choices are shown as the next eight decisions. Should a low stream flow (1) occur, 804 acres of the 1308 acres of soybeans are watered for a low stress level while 504 acres are watered for a high stress level. Should a medium stream flow be observed 852 and 456 acres are watered to the low and high stress levels respectively. Should a high stream flow be observed, all 1308 acres are watered to a low stress level.

The second period decision is again based upon low, medium, and high (1, 2, and 3 respectively) stream flows observed in the second period. Space does not permit a full discussion. However, for example, of the 804 acres irrigated at the low stress level in Period 1, a low stream flow occurring in Period 2 results in 627 acres irrigated to the low stress level and 177 acres abandoned. When medium and high stream levels occur, no abandonment takes place.

Increased target stream flow minimums are clearly observed to reduce the objective function, reduce crop acreage, and <u>generally</u> increase soybean acreage and reduce grain sorghum acreage. This issue of crop mix is obviously complex because it is coupled to slack choice.

Conclusions

In this analysis, evaluation of irrigation decisions involving initial crop choice and conditional abandonment is done in a framework of requiring varying probabilities of varying remaining target stream flow minimums. These target stream flow minimums may be desired for objectives other than irrigation such as environmental protection. The enforcement of probabilities to violate target minimums is accomplished through zero-one safety-first programming.

A probability based target minimum stream flow concept may well be preferred to simple non-probability based requirements for maintaining minimum stream flows. Were the latter concept preferred, this is a subset of the analysis (zero percent or Table 6). Alternatively this zero percent concept could be accomplished by removing the stream flow minimums from the right hand sides and use ordinary DSP to solve the problem. However, the use of probability-based programming enriches the analysis set.

Table 1. Initial and Conditional Crop and Irrigation Strategies (In Acres) With No Stream Flow Minimum Requirements (Objective Function $136,266).

	Decision[1]	
Initial Crop Decision	B	1131
	C	691
First Irrigation Decision	B1L	1131
	B2L	1131
	B3L	1131
	C1L	691
	C2H	691
	C3L	691
Second Irrigation Decision	B1L1L	1131
	B1L2L	1131
	B1L3M	1131
	B2L1L	1131
	B2L2L	1131
	B2L3L	198
	B2L3H	933
	B3L1L	1131
	B3L2L	1131
	B3L3L	198
	B3L3H	933
	C1L1ab	(691)[2]
	C1L2M	691
	C1L3L	691
	C2H1ab	(691)
	C2H2H	691
	C2H3H	691
	C3L1ab	(691)
	C3L2M	691
	C3L3H	691

[1] Read as crop a, b, or c, probability of stream flow being low (1), medium (2), or high (3) in period 1, irrigation stress strategy in period 1 (high, medium, or low stress, probability of stream flows in period 2, and irrigation stress strategy in period 2, respectively.

[2] Acres in parentheses refer to abandonment.

Table 2. **Initial and Conditional Crop and Irrigation Strategies (In Acres) for Six Equal Remaining Stream-Flow Requirements in Two Periods Where Probability of Failing to Meet Stream Flow Targets is 90%.**

Target For Remaining Stream Flows (Acre Feet)

Decision[1]	0	1000	1200	1400	1600	1800	Period 1
	0	1000	1200	1400	1600	1800	Period 2
Objective Function ($)	136,266	135,940	134,325	125,375	105,660	85,311	
B	1131	1200	1500	1174	1131	1131	
C	691	587	213	235	235	235	
B1L	1131	808	1056	649	598	598	
B1H		391	443	526	533	533	
B2L	1131	1131	1131	718	675	675	
B2H		69	369	456	456	456	
B3L	1131	1200	1500	1184	1131	1131	
C1L	691	587	132	213	235	235	
C2H	691	587	132	213	235	235	
C3L	691	587	132	213	235	235	
B1L1ab		(69)[2]	(369)	(44)			
B1L1L	1131	739	687	605	598	598	
B1L2L	1131	808	1056	649	598	598	
B1L3M	1131	808	1056	649	598	598	
B1H1L		391	443	526	533	533	
B1H2L		249					
B1H2M		142	297	334	344	344	
B1H2H			147	192	189	189	
B1H3H		391	443	527	533	533	
B2L1L	1131	1131	1131	718	675	675	
B2L2L	1131	1131	1131	718	675	675	
B2L3ab					(538)	(663)	
B2L3L	198	1131	327	718	137	12	
B2L3H	933		804				
B2H1M		69	369	456	456	456	
B2H2L		69	369	456	456	456	
B2H3ab						(456)	
B2H3L		69		456	456		
B2H3H			369				

Table 2 (continued)

Decision[1]	0	1000	1200	1400	1600	1800	Period 1
	0	1000	1200	1400	1600	1800	Period 2
B3L1ab		(69)	(369)	(43)			
B3L1L	1131	1131	1131	1131	1131	1131	
B3L2L	1131	1057	738	233	189	189	
B3L2M		142	762	942	942	942	
B3L3L	198	222	1500				
B3L3H	933	978		1174	1131	1131	
C1L1ab	(691)	(587)	(132)	(213)	(235)	(235)	
C1L2M	691	587	132	213	235	235	
C1L3L	691	587	132	213	235	235	
C2H1ab	(691)	(587)	(132)				
C2H1L				213	235	235	
C2H2H	691	587	132	213	235	235	
C2H3ab			(213)	(235)	(235)		
C2H3H	691	587	132				
C3L1ab	(691)	(587)	(132)	(213)	(235)	(235)	
C3L2M	691	587	132	213	235	235	
C3L3H	691	587	132	213	235	235	

[1] Read as crop a, b, or c, probability of stream flow being low (1), medium (2), or high (3) in period 1, irrigation stress strategy in period 1 (high, medium, or low stress, probability of stream flows in period 2, and irrigation stress strategy in period 2 respectively.

[2] Acres in parentheses refer to abandonment.

Table 3. **Initial and Conditional Crop and Irrigation Strategies (In Acres) for Six Equal Remaining Stream-Flow Requirements in Two Periods Where Probability of Failing to Meet Stream Flow Targets is 60%.**

Target For Remaining Stream Flows (Acre Feet)

Decision[1]	0	200	400	600	800	850	Period 1
	0	200	400	600	800	850	Period 2
Objective Function ($)	136,266	134,112	127,456	110,123	89,936	84,943	
B	1131	1431	1308	1131	1131	1131	
C	691	237	144	235	218	196	
B1L	1131	999	804	712	985	1131	
B1H		432	504	418	145		
B2L	1131	1131	852	675	708	750	
B2H			456	456	422	381	
B3L	1131	1431	1308	1131	1131	1131	
C1L	691	237	144	235	218	196	
C2L				79	218	196	
C2H	691	237	144	156	218	196	
C3L	691	237	144	235	218	196	
B1L1ab		(300)[2]	(177)				
B1L1L	1131	699	627	712	985	1131	
B1L2ab					(985)	(985)	
B1L2L	1131	999	804	712			
B1L3M	1131	999	804	712	985	1131	
B1H1L		432	504	418	145		
B1H2L					145		
B1H2M		345	302	177			
B1H2H		87	202	241			
B1H3H		432	504	418	145		
B2L1L	1131	1131	852	675	708	750	
B2L2L	1131	1131	852	675	603	514	
B2L2M					105	236	
B2L3L	198	198	13	31			
B2L3L					249	326	
B2L3H	933	933	839	643	459	424	
B2H1M			456	456	422	381	
B2H2L			456	456	422	381	
B2H3L			456	456	422	381	

Table 3 (continued)

Decision[1]	0 0	200 200	400 400	600 600	800 800	850 850	Period 1 Period 2
B3L1ab		(300)	(177)				
B3L1L	1131	1131	1131	1131	1131	1131	
B3L2ab				(404)			
B3L2L	1131	1431	1308	727	153	109	
B3L2M					977	1022	
B3L3L	198	498	469	487	672	706	
B3L3H	933	933	839	643	459	424	
C1L1ab	(691)	(237)	(144)	(235)	(218)	(196)	
C1L2ab					(218)	(196)	
C1L2M	691	237	144	235			
C1L3L	691	237	144	235	218	196	
C2L1L				79	218	196	
C2L2M				79	218	196	
C2L3H				79	218	196	
C2H1ab	(691)	(237)	(144)				
C2H1L				156			
C2H2H	691	237	144	156		235	
C2H3H	691	237	144	156		235	
C3L1ab	(691)	(237)	(144)	(235)	(218)	(196)	
C3L2ab			(144)	(235)			
C3L2M	691	237			218	196	
C3L3H	691	237	144	235	218	196	

[1] Read as crop a, b, or c, probability of stream flow being low (1), medium (2), or high (3) in period 1, irrigation stress strategy in period 1 (high, medium, or low stress, probability of stream flows in period 2, and irrigation stress strategy in period 2 respectively.

[2] Acres in parentheses refer to abandonment.

Table 4. **Initial and Conditional Crop and Irrigation Strategies (In Acres) for Six Equal Remaining Stream-Flow Requirements in Two Periods Where Probability of Failing to Meet Stream Flow Targets is 50%.**

	Target For Remaining Stream Flows (Acre Feet)						
Decision[1]	0 0	200 200	400 400	600 600	800 800	850 850	Period 1 Period 2
Objective Function ($)	136,266	132,990	123,797	92,480	52,846	43,108	
B	1131	1431	1308	1131	1131	1131	
C	691	237	237	9	144	235	
B1L	1131	999	756	5193	985	1131	
B1H		432	552	612	145		
B2L	1131	1131	1131	1131	1131	1131	
B2H		300	177				
B3L	1131	1431	1308	1131	1131	1131	
C1L	691	237					
C2H	691	237					
C3L	691	237					
B1L1ab		(300)[2]	(178)				
B1L1L	1131	699	578	579	985	1131	
B1L2ab					(985)	(1131)	
B1L2L	1131	999	756	519			
B1L3M	1131	999	756	519	985	1131	
B1H1L		432	552	612	145		
B1H2L		432	552		145		
B1H2M				376			
B1H2H				376			
B1H3H		432	552	612	145		
B2L1L	1131	1131	1131	1131	1131	1131	
B2L2ab				(404)	(986)	(1131)	
B2L2L	1131	1131	259	747	145		
B2L2M			872				
B2L3L	198	198	198	334	530	578	
B2L3H	933	933	933	797	601	552	
B2H1M		300	177				
B2H2L		300	177				
B2H3L		300	177				

Table 4 (continued)

Decision[1]	0 0	200 200	400 400	600 600	800 800	850 850	Period 1 Period 2
B3L1ab		(300)	(177)				
B3L1L	1131	1131	1131	1131	1131	1131	
B3L2ab				(404)		(137)	
B3L2L	1131	1431	1308	727			
B3L2M					994	994	
B3L2H					137	137	
B3L3L	198	498	376	334	530	579	
B3L3H	933	933	933	797	601	552	
C1L1ab	(691)	(237)					
C1L2M	691	237					
C1L3L	691	237					
C2H1ab	(691)	(237)					
C2H2H	691	237					
C2H3H	691	237					
C3L1ab	(691)	(237)					
C3L2M	691	237					
C3L3H	691	237					

[1] Read as crop a, b, or c, probability of stream flow being low (1), medium (2), or high (3) in period 1, irrigation stress strategy in period 1 (high, medium, or low stress, probability of stream flows in period 2, and irrigation stress strategy in period 2 respectively.

[2] Acres in parentheses refer to abandonment.

Table 5. **Initial and Conditional Crop and Irrigation Strategies (In Acres) for Five Equal Remaining Stream-Flow Requirements in Two Periods Where Probability of Failing to Meet Stream Flow Targets is 30%.**

	Target For Remaining Stream Flows (Acre Feet)					
Decision[1]	0	100	200	300	389	Period 1
	0	100	200	300	389	Period 2
Objective Function ($)	136,266	126,612	111,178	95,707	82,072	
B	1131	1131	1131	1131	1131	
C	691	251			108	
B1L	1131	701	714	812	1131	
B1H		430	416	319		
B2L	1131	840	740	889	1131	
B2H		291	391	241		
B3L	1131	1131	1131	1131		
C1L	691	251			108	
C2H	691	251			108	
C3L	691	251			108	
B1L1ab					(1131)[2]	
B1L1L	1131	701	714	812		
B1L2L	1131	701	714	812	1131	
B1L3M	1131	701	714	812	1131	
B1H1L		430	415	319		
B1H2M		351	236	236		
B1H2H		79	181	83		
B1H3H		406	416	319		
B2L1ab			(191)	(630)		
B2L1L	1131	840	549	259	1131	
B2L2L	1131	840	740	889	1131	
B2L3L	198		41	198	198	
B2L3H	933	840	740	849	933	
B2H1M		291	391	241		
B2H2L		291	391	241		
B2H3L		9				
B2H3H		282	391	241		

Table 5 (continued)

Decision[1]	0	100	200	300	389	Period 1
	0	100	200	300	389	Period 2
B3L1L	1131	1131	1131	1131		
B3L2L	1131	531	323	632	1131	
B3L2M		600	808	498		
B3L3L	198	9		41	198	
B3L3H	933	1122	1131	1090	933	
C1L1ab	(691)	(251)			(108)	
C1L2M	691	251			108	
C1L3L	691	251			108	
C2H1ab	(691)	(251)			(108)	
C2H2H	691	251			108	
C2H3H	691	251			108	
C3L1ab	(691)	(251)			(108)	
C3L2M	691	251			108	
C3L3H	691	251			108	

[1] Read as crop a, b, or c, probability of stream flow being low (1), medium (2), or high (3) in period 1, irrigation stress strategy in period 1 (high, medium, or low stress, probability of stream flows in period 2, and irrigation stress strategy in period 2 respectively.

[2] Acres in parentheses refer to abandonment.

Table 6. **Initial and Conditional Crop and Irrigation Strategies (In Acres) for Five Equal Remaining Stream-Flow Requirements in Two Periods Where Probability of Failing to Meet Stream Flow Targets is 0%.**

Target For Remaining Stream Flows (Acre Feet)

Decision[1]	0	100	200	300	389	Period 1
	0	100	200	300	389	Period 2
Objective Function ($)	136,266	106,033	75,801	45,568	18,661	
B	1131	840	549	259		
C	691	691	691	691	691	
B1L	1131	461	170	259		
B1H		380	380	259		
B2L	1131	840	549	259		
B3L	1131	840	549	259		
C1L	691	691	691	691	691	
C2H	691	691	691	691	691	
C3L	691	691	691	691	691	
B1L1ab				(259)[2]		
B1L1L	1131	461	170			
B1L2Lab				(259)		
B1L2L	1131	461	170			
B1L3ab				(259)		
B1L3M	1131	461	170			
B1H1L		380	380	259		
B1H2L		380	380	259		
B1H3H		380	380	259		
B2L1L	1131	840	549	259		
B2L2L	1131	840	549	259		
B2L3L	198	840	549	259		
B2L3H	933	840	549	259		
B3L1L	1131	840	549	259		
B3L2L	1131	840	549	259		
B3L3L	198	840	549	259		
B3L3H	933	840	549	259		
C1L1ab	(691)	(691)	(691)	(691)	(691)	
C1L2M	691	691	691	691	691	
C1L3L	691	691	691	691	691	

Table 6 (continued)

Decision[1]	0 0	100 100	200 200	300 300	389 389	Period 1 Period 2
C2H1ab	(691)	(691)	(691)	(691)	(691)	
C2H2H	691	691	691	691	691	
C2H3H	691	691	691	691	691	
C3L1ab	(691)	(691)	(691)	(691)	(691)	
C3L2M	691	691	691	691	691	
C3L3H	691	691	691	691	691	

[1] Read as crop a, b, or c, probability of stream flow being low (1), medium (2), or high (3) in period 1, irrigation stress strategy in period 1 (high, medium, or low stress, probability of stream flows in period 2, and irrigation stress strategy in period 2 respectively.

[2] Acres in parentheses refer to abandonment.

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Modeling Irrigation Decisions and Stream Flow Minimums: An Application of Discrete Stochastic Programming and Zero-One Safety First Programming - Discussion[1]

Harry M. Kaiser[2]

Helmers, Atwood, and Javed have chosen an excellent application for risk programming, as uncertainty over water availability for crop production is an important issue in this region. Moreover, this issue will likely become even more important in the future. This paper is also the latest empirical study that uses discrete stochastic programming (DSP). Although DSP has been around since the late 1960s (Cocks), the number of empirical studies in agriculture that utilize this technique is still relatively small. This is somewhat surprising, since the unique characteristics of agricultural decision making seem to be ideally suited for DSP. This paper briefly summarizes and discusses Helmers, Atwood, and Javed's study.

DSP is basically a mathematical programming formulation of a decision tree. The decision making process is divided into discrete stages, and within each stage discrete random events (states of nature) may occur. At the beginning of each decision stage, an agent makes a decision based on: (1) the observed outcome of states in previous stages, (2) plans implemented in previous stages, and (3) probabilistic knowledge of states in future stages. DSP is flexible enough to handle a wide array of information structures, including: (1) complete information of the past and present, where the agent has perfect knowledge of which states have occurred in previous stages as well as the current stage; (2) complete information of the past, where the decision maker has complete knowledge of which previous states have occurred, but only probabilistic knowledge of current and future states; and (3) incomplete information of the past, where the agent does not know the outcome of some earlier states of nature (Kaiser and Apland).

Helmers, Atwood, and Javed divide the decision making environment for irrigated agriculture in Nebraska into two stages. In stage 1, the decision maker decides upon what crops to grow and the water level that is to be maintained. The choice of crops include corn, soybeans, and sorghum while the choice of water levels include low, medium, and high stress levels (where low stress requires the most water and high stress requires the least water). Three discrete states of nature, defined by low, medium, and high stream flows, are assumed to occur in stage 1 with equal probability. In stage 2 of the authors' model, the decision maker decides on which of the three water levels should be maintained for the second stage. This decision is a function of several factors, including: 1) the choice of crops and water levels made in stage 1, (2) which of the three stage 1 states has occurred, and (3) the discrete probability distribution of the stage 2 states of nature. It is assumed that stage 2 has three equally likely discrete states of nature defined by low, medium, and high stream flows, whose occurrence is independent from the stage 1 states. Consequently there are nine joint events in total. The authors assume an information structure of complete information of past events.

One of the advantages of using DSP over most conventional risk programming models (e.g., traditional quadratic programming and MOTAD models) is that in addition to parameters in the objective function, parameters in the constraint set can also be treated as

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stochastic. Hence, in addition to price and yield risk, which is modeled by treating objective function coefficients as random variables, important sources of uncertainty in the constraint set can also be modeled. For example, in the present model, the authors model water availability as a stochastic (discrete) right-hand-side parameter, which is another important source of risk to farmers. In other studies using DSP, field time and resource usage have been modeled stochastically as states of nature on right-hand-side and technical coefficients (e.g., Rae; Kaiser and Apland; Klemme).

Another contribution of Helmers, Atwood, and Javed's study is that it combines a zero-one integer safety first model with the DSP model. Safety first models constrain the actions of the decision maker in such a way that the probability of failing to achieve certain goals is minimized. While most applications of this technique use targeted income levels as the goal, stream flow minimum goals are used in Helmers, Atwood, and Javed's study. This feature of the model is important for agents having strong preferences for insuring the probability of maintaining particular levels of stream flows.

The results of the authors' model are interesting in a farm management sense because they provide optimal contingency plans corresponding to each stage 1 state of nature. For example, based on the observance of say the medium state of nature of water flows in stage 1, the decision maker should follow a certain stage 2 strategy that is optimal. While these results are interesting, they are also difficult to understand given the complexity of the notation. Even in this relatively small two stage, three state of nature problem, the notation for some of the variables have up to four subscripts. Hence, some work would be needed on the presentation of results if the model were to be utilized for farm management extension purposes.

There are several improvements that I believe could be made that would make this model more realistic. The following briefly summarizes my suggestions for modifications in the model.

First, the model is probably too small in terms of approximating the decision making environment of farmers in this region. Currently, the riskiness of stream flows in each stage is captured by only three states of nature. Given that there are two stages, this makes nine independent joint states of nature in total. There is no question that more states of nature could be added without adding computational problems. I suggest that a more appropriate number would be closer to 10 states of nature for each stage, which would result in a total of 100 joint states of nature. On the other hand, one might also argue that there are not enough decision stages in this model. This model could have easily been made a three stage problem, where stage 1 would be the planting stage, stage 2 would be the post-plant-pre-harvest stage, and stage 3 would be the harvest stage. While some sacrifice would have to be made on the number of states of nature in each stage, one could still have a model that was larger than the current three state formulation without incurring computational problems. Incidentally, there is no requirement that the number of states of nature have to be equal for each stage. Indeed, one might even treat the first stage deterministically if the level of risk in that stage is not that important in the problem.

Second, price risk should be incorporated into the model. While variability of stream flows is undoubtedly an important source of risk to farmers, price risk is equally, if not more important. The exclusion of price risk in the model probably biases the crop mix results. Therefore, I suggest that future versions of this model incorporate discrete price states of nature in addition to stream flows. While I realize that the focus of this study is on irrigation and crop mix decisions, price risk is too important to the decision process to leave out. This is especially important if the model is to be used in evaluating crop choice decisions.

Third, the authors (admittedly so) should have included dryland agricultural activities in the model. This would have made for more flexible activities in response to the random stream flow states. It would have also made the model more realistic because a combination of irrigated and dryland crops would be one way to spread out some of the risk of stream flow variability.

Fourth, the current model assumes that the decision maker is a risk neutral, profit maximizing agent. The model should be altered to include risk aversion behavior. The modifications to the current model to include risk aversion would be easy to make. Consequently, I would recommend making such changes in future versions of the model since many farmers in this region are likely risk averse.

Finally, I would have liked to have seen a greater level of disaggregation of activities in terms of the field operations required to produce the crops and in terms of the number of time periods that operations can be performed in each stage. For example, within each of the two stages, field operations such as plowing, planting, and harvesting could have been specified with a schedule of periods that each operation could be performed. By disaggregating the activities by operation and time period, the timing of field operations would be explicit in the model. This is important because there are times in the year where bottlenecks occur, which influence such important decisions as choice of crops to produce.

In general, however, Helmers, Atwood, and Javed have done a good job of extending the DSP technique to the important area of irrigation decision making. It is a useful contribution to the literature on empirical applications of DSP.

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ESTIMATES OF TREND AND VARIABILITY PATTERNS IN U.S. CROP YIELD SERIES

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INTRODUCTION

When estimating moments of yield probability distributions from time series data, the analyst faces a large number of practical methodological decisions (Young 1980, 1984). How long a time period of data should be used? Should conditioning variables, such as weather, and productive input levels (chemicals, irrigation, etc.) be included? What functional forms should be employed to remove any systematic trend in the data? How should the trend component and residual variability component be estimated? Are crop yield distributions heteroskedastic, autocorrelated, or skewed? Are second and higher order moments stable or varying over time?

The first and most obvious problem in modeling yields is that there is trend (generally upward) due to technological advances and increased capitalization and use of purchased inputs. This trend, however, is not necessarily linear in time. Indeed, as Griliches pointed out, yield trend can be expected to be S-shaped over periods when significant new technological developments are adopted, as with the introduction of hybrid corn in the 1940s. If trend is taken to be a deterministic function of time, the question of the choice of a functional form arises. Other methods, such as moving average and stochastic trend methods can also be employed, though they have their own problems (Moss and Boggess, Fackler).

A second problem is that there are often significant differences in the variability of yields in different periods, with the absolute level of variability tending to rise as mean yields rise. Whether a standardized measure, such as the coefficient of variation, has risen is not so clear. To properly model the current yield risk, potential heteroskedasticity should be addressed; however, most past empirical estimates of yield variability have assumed homoskedasticity and have employed ordinary least squares (OLS) estimators of trend equations (Anderson and Hazell).

The overall shape of the yield probability distribution, and particularly its skewness characteristics, also must be considered. It is generally recognized that crop yields often exhibit considerable negative skewness (Gallagher, Day). Relatively infrequent drought conditions (e.g., 1974, 1983 and 1988), or unusual pest conditions (e.g., Southern corn blight in 1970) can cause significantly lower than average yields. Estimation methods that give equal weight to positive and negative deviations from means can conceal important information about the nature of yield trends and risks. Also, OLS, GLS, or other methods based on least squares will tend to be strongly influenced by large deviations, particularly if these occur near either end of the sample period (the 1988 U.S. Midwest drought, for example).

Autocorrelation can also be present, for a number of reasons. Droughts tend to have multiyear effects in areas where soil moisture is not replenished in a single year. Also, new varieties of crops and new methods of pest control will tend to have the greatest impact on yields soon after introduction. After a time, pests evolve adaptations and reassert themselves (Carlson).

This paper reports empirical results of an effort to model crop yield trends for 75 U.S. regional data series. These data, measured over forty years, will be used to identify the importance of, and potential solutions to, some of the important empirical issues discussed above. The results of this analysis could be used in an aggregate U.S. agricultural sector model to derive endogenous price probability distributions for each crop under alternative policy scenarios (McCarl et al.). Frequently, a risk neutral specification is used in the objective function of such aggregate models. Theoretically, one might describe the process as tracing out the effects on price of stochastic shifts in the supply curves of commodities due to yield variability. Because this descriptive process does not represent an attempt to predict the behavior of individuals in response to risk perceptions, the use of objective time series and statistical procedures to measure risk is appropriate (Fackler and Young).

Although it might seem obvious, it is important to note that regional time series data such as that used in this study generally will not provide yield probability distribution parameters appropriate for farm-level studies. As shown by Carter and Dean, yield variability estimates will generally be lower at higher levels of geographic aggregation. Furthermore, absolute levels and trend patterns of yields can differ greatly from one local region to another.

Specifically, a model is estimated that is a quadratic function of time in both its mean and in the standard deviation of its residuals and that exhibits first order autocorrelation in the normalized residual. Maximum likelihood estimation is used, which facilitates hypothesis testing using well known asymptotic results. In particular, Wald tests are computed to test for heteroskedasticity, serial correlation, and time variation in the coefficient of variation. Also normality tests are conducted on model residuals.

The use of a flexible model and a battery of tests on a relatively large number of yield samples provides an assessment of what kinds of departures from standard models are most frequent and most serious in crop yield models. Past studies have either used highly restrictive models specifications, generally using OLS (Anderson and Hazell), have used more flexible modeling procedure for a single crop example (Gallagher, Yang, et al.) or have employed complex models that are difficult to apply or make inferences from many time series (Moss and Boggess).

METHODOLOGY: STATISTICAL ESTIMATORS

As already discussed, there are a number of reasons why it is likely that crop yields (y_t) display quadratic trends in both their means and their standard deviations and may also display serial correlation in their deviations from mean. An explicit model of these phenomena can be written:

$$e_t = y_t - x_t'\beta,$$

where

$$\frac{e_t}{x_t'\alpha} = \rho \frac{e_{t-1}}{x_{t-1}'\alpha} + v_t,$$

with $Var(v_t)=1$. Here x_t includes a constant, a trend term and a trend squared term and α, β and ρ are parameters to be estimated. The model implies that

$$E\left[\left(\frac{e_t}{x_t'\alpha}\right)^2\right] = \frac{1}{1-\rho^2}$$

and

$$E\left[\left(\frac{e_t}{x_t'\alpha}\right)\left(\frac{e_{t-1}}{x_{t-1}'\alpha}\right)\right] = \frac{\rho}{1-\rho^2}$$

It is further assumed that the v_t are normally and independently distributed (the results of tests of this assumption are discussed below). ML estimates of the parameters of this model were calculated.[1] An appendix provides details on the distribution theory for this estimator.

The ML estimates were then used to construct Wald tests for the hypotheses of constant residual variance, constant residual coefficient of variation and lack of serial correlation. Intuitively these tests attempt to determine whether the unrestricted parameter estimates satisfy a given set of restrictions. To simplify the discussion, suppose that we write the complete set of model parameters as $\theta=[\beta' \ \alpha' \ \rho]'$. A set of restrictions (possibly non-linear) can be written as $r(\theta)=0$, where R represents a set of independent functional relationships (i.e., $R(\theta)\equiv\partial r(\theta)/\partial\theta$ has full row rank). The Wald statistic associated with these restrictions is

$$w = r(\theta)'[R(\theta)I(\theta)^{-1}R(\theta)']^{-1}r(\theta).$$

This statistic has (asymptotically) a χ^2 distribution with degrees of freedom equal to the number of rows in $R(\theta)$.

Four such tests are conducted on the yield data. The first is that yields are both homoskedastic and exhibit no serial correlation, implying that

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1. There is a possibility of negative estimates of $z_t'\alpha$ for some values of t. To avoid this a penalty function was subtracted from the loglikelihood to bound α away from the negative $z_t'\alpha$ region. The penalty function used here was

$$\text{penalty}=\frac{\sigma_{OLS}}{n}\sum_{t=1}^{n}\frac{1}{z_t'\alpha}$$

A similar problem exists for ρ, which should lie on the $[-1,1]$ interval. This can be most easily handled by defining an unrestricted variable, ρ^*, and calculating ρ using

$$\rho = \frac{\rho^*}{1+|\rho^*|}$$

$$r(\theta) = (\alpha_1\ \alpha_2\ \rho)^T$$

and

$$R(\theta) = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}.$$

Rejection of this test would indicate that OLS is perhaps not an appropriate estimation strategy and, more particularly, that estimated covariances of OLS coefficient estimates will be biased.

Two more specific tests can be conducted to provide evidence on the source of the rejection. The hypothesis of homoskedasticity can be examined using

$$r(\theta) = (\alpha_1\ \alpha_2)'$$

and

$$R(\theta) = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}.$$

whereas the hypothesis of no serial correlation can be tested using

$$r(\theta) = \rho$$

and

$$R(\theta) = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}.$$

The fourth test conducted is that the yields exhibit constant coefficient of variation (CV). The CV at time t in this model is given by

$$CV_t = \frac{x_t'\alpha}{x_t'\beta}.$$

If α and β are proportional to one another this term will be constant over time. This hypothesis implies nonlinear restrictions on the coefficients of the form

$$\frac{\alpha_0}{\beta_0} = \frac{\alpha_1}{\beta_1} = \frac{\alpha_2}{\beta_2}.$$

Nonlinear restrictions can be written in a variety of forms that are equivalent under the null hypothesis but not under the alternative. The Wald test statistic, which is based on unrestricted coefficient estimates, is not invariant to arbitrary choices of the form in which the restrictions are written. For example, the above restrictions can be written

1: $\alpha_0\beta_1-\alpha_1\beta_0=0$

2: $\alpha_0\beta_2-\alpha_2\beta_0=0$

3: $\alpha_1\beta_2-\alpha_2\beta_1=0$

with associated derivatives

1: $\begin{bmatrix}-\alpha_1 & \alpha_0 & 0 & \beta_1 & -\beta_0 & 0 & 0\end{bmatrix}$

2: $\begin{bmatrix}-\alpha_2 & 0 & \alpha_0 & \beta_2 & 0 & -\beta_0 & 0\end{bmatrix}$

3: $\begin{bmatrix}0 & -\alpha_2 & \alpha_1 & 0 & \beta_2 & -\beta_1 & 0\end{bmatrix}$

Any two of these three restrictions can be used to test the constant CV hypothesis. The test is conducted using all three possible combinations of the three forms of the restrictions: (1,2), (1,3) and (2,3).

A final set of tests are conducted to examine the normality assumption. The tests used are discussed by D'Agostino, Belanger and D'Agostino, and involve the use of the standardized third and fourth moments of the regression residuals. In a normally distributed sample these should equal 0 and 3, respectively. Three tests are performed, one to test whether the sample exhibits skewness, the second to test for nonnormal kurtosis and the third a joint test that combines the first two.

DATA

The 75 regional crop yield data series utilized in this chapter were drawn from the following 9 major crops and 10 standard USDA regions:

Crops		Regions	
1.	Wheat	1.	Pacific
2.	Rice	2.	Northern Plains
3.	Corn	3.	Northeast
4.	Oats	4.	Lake
5.	Barley	5.	Corn Belt
6.	Sorghum	6.	Appalachian
7.	Cotton	7.	Southeast
8.	Soybeans	8.	Delta
9.	Hay	9.	Delta Plains
		10.	Mountain

All data were collected by the National Agricultural Statistics Service (NASS) of the U.S. Department of Agriculture. The following region-crop combinations were excluded due to small or nonexistent acreages: rice in the Northern Plains, Northeast, Lake, Appalachian, Southeast, and Mountain regions; barley in the Corn Belt and Delta regions; sorghum in the Northeast and Lake regions; cotton in the Northeast, Lake, and Northern Plains regions; and soybeans in the Mountain and Pacific regions.

LENGTH OF DATA PERIOD

Estimates were generated for both a 40-year time series (1950-89) and a 30 year period (1960-89). In order to keep the length of this paper manageable detailed results of sample size comparisons are not presented but a few conclusions are summarized. Overall, the 40-year time series appeared to generate more "reasonable" quadratic trend lines than the 30-year time series. The shorter time series is more vulnerable to "outliers" near the endpoints of the estimated equations. This resulted in strongly convex "bowl-shaped" 30-year trend lines for several crops (e.g., Pacific cotton and Mountain and Northern Plains barley). However, a different pattern of endpoint outliers can also result in strongly concave short-period trend lines relative to the longer period as evidenced by Southern Plains hay.

Taken collectively, the 30-year versus 40-year trend comparisons serve as a strong reminder of the importance of the length and location of sample data periods. Many researchers will regard 30 years of yield data as a relatively long time series for applied research, but the results discussed here indicate that even longer time series should be sought for crops which have experienced an erratic yield growth pattern. Of course, if the crop yield time series is relatively smooth and uniform (e.g., Pacific or Northern Plains wheat) the length of the sample period exerts much less influence on estimated yield trends. Over half of the regional yield time series examined exhibit such smooth yield growth patterns.

The length of the sample period can exert a critical influence on important substantive conclusions regarding the nature of yield trends and variability patterns. Singh and Byerlee (1990) used a longer data period to refute many of the conclusions reached by Anderson and Hazell that yield variability had increased in many developing nations following the Green Revolution. Using a longer span of years following the Green Revolution, Singh and Byerlee confirmed that risk measured as coefficient of variation had actually declined in most areas.

TEST RESULTS

Coefficient estimates for all crop-region combinations, as well as detailed test results are available from the authors. The test results are summarized in Table 1, which presents the number of times (out of the 75 crop/region samples) a pair of tests indicated rejection at the 0.05 level. For example, the first diagonal element of this table indicates that the omnibus likelihood ratio (LR) test rejected the hypothesis of homoskedasticity and no serial correlation 53 out of 75 times.

The off diagonal value associated with the LR and the associated Wald test (test 2) that 48 times both tests rejected this hypothesis. This further implies that in 5 cases the LR test rejected when the Wald did not and in 8 other cases the Wald test rejected when the LR did not. Table 2 highlights the major test results and Table 3 provides detail on specific crop and regions.

A large number of the samples exhibited evidence that standard assumptions are not valid in crop yield modeling. In 75% of the cases either homoskedasticity or serial independence was rejected. Sixty percent of the samples rejected homoskedasticity and, although these rejections were not isolated to a particular geographical region, corn and barley in particular exhibited this property.

Changing degrees of residual variability should not in itself be taken to indicate changing degrees of risk, given that mean yields have generally been increasing over the period examined. The coefficient of variation (CV) may be a better measure of risk. The case for changes in CV over time is much weaker. Between 29 and 36% of the samples rejected the hypothesis that the CV was constant over the sample period (as discussed above, Wald tests of this nonlinear restriction are not unique). These rejections, furthermore, were not specific to particular crops. Also two regions (Pacific and Northern Plains) together exhibited only one rejection of constancy of CV.

One conclusion to be drawn from the finding that constant CVs are more generally found than constant variances is that, in situations in which a modelling choice must be made between additive and multiplicative residuals, it may be safer to chose multiplicative ones. The multiplicative error model (when the errors are identically distributed) imposes constancy of CV. This is in contrast to a similar additive error model, which imposes constancy of variance.

Autocorrelation was also found in a large number of samples (47%). Its presence was not confined to any region but was particularly concentrated in cotton, sorghum and rice (18 of 19 samples). Soybeans and oats, on the other hand, each exhibited autocorrelation in only one of the regions. Clearly autocorrelation is a property that deserves to be recognized in crop yield modeling. It is likely that the first order framework used here, in fact, does not adequately represent the serial correlation exhibited by crop yields. Pest induced serial correlation, in particular, is likely to display more complex cyclical behavior that a first order model cannot represent. Spatial aggregation also can influence measurement of autocorrelation related to moisture and pest damage. This could be investigated by studying state or county level yields.

Somewhat surprising are the results on normality. Only 11% of the samples rejected normality of the errors. Furthermore the rejections were in relatively minor production areas. In part this is a function of the degree of spatial aggregation. Mean regional yields, being fairly highly aggregated, are more likely to be affected by central limit properties than are farm or county yields.

An interesting comparison can be made, however, between the frequency of rejection of normality when ML residuals are tested and when OLS residuals are tested. In the latter case fully a third of the samples rejected normality. The ML residuals, which are adjusted to reflect the heteroskedasticity and autocorrelation, are far less likely to exhibit nonnormalities. This has an important implication for modeling strategies. It is often the case that rejection of a particular test is the result of a problem other than the one specifically being tested. In this case an analyst who only tested for normality using OLS residuals would often have concluded that nonnormality is a relatively common occurrence in crop yields. By not performing a whole set of tests designed to identify other probable violations of standard assumptions, such an analyst would have drawn incorrect conclusions.

OLS VERSUS ML

The comparison of the ML and OLS estimators is of interest more generally, given the widespread use of OLS. One conclusion that can be drawn by examining predicted yields (not shown) from the two models is that quadratic trend lines are generally very close to one another, especially when the full forty year sample period is used. Therefore, the presence of autocorrelation or heteroskedasticity does not appear to bias estimates of yield trend.

A significant advantage of the ML estimation procedure used here is that it permitted estimation and testing of patterns of trends in yield variability. Even a casual inspection of the scatter of annual yield data points in several of the time series suggests that heteroskedasticity might be present. Increasing yield variability through time seems to be present, for example, for Appalachian sorghum, Northern Plains soybeans, Great Lakes corn, and Southeast wheat, among others. A few time series depart from the common pattern of increasing yield variability through time. For example, Delta soybeans exhibited high yield variability in the 1950s followed by relatively low yield variability in the 1960s through the mid-1970s followed by somewhat higher recent yield variability.

The OLS and ML estimators give very different estimates of yield variability. The OLS approach implicitly assumes that the error standard deviation is constant over time. The ML model, on the other hand, provides an estimate of the standard deviation at each point in time conditional on the previous period's yield (the conditioning comes from the autocorrelation factor).

Table 4 provides a comparison of the risk estimates from the two approaches for the first post-sample year (1990). This is measured as the ratio of the OLS to the ML standard deviations. Overall, in the 75 cases, this ratio had an average of 0.78, indicating that the OLS approach tended to underestimate yield variability for 1990. This pattern was generally true when the ratio was averaged over crop or regions as well; the only exceptions being rice and hay and the Northeast region. In some cases the comparison between the two estimators was quite dramatic. In Cornbelt corn and soybeans, for example, the OLS estimate was only half of the ML estimate. On the other hand, for Northeast hay the OLS standard deviation was four and a half times the ML estimate.

The main reason OLS estimates are generally lower than ML is that yield variability has generally been increasing. The OLS measure can be thought of as an estimate of the average variability over the sample. In situations in which variability is higher than average at the end of the sample, OLS will tend to underestimate the variability for end-of-sample periods.

CONCLUSIONS

The preceding empirical analysis of regional crop yield trends and standard deviations clarifies several general issues. First, because of the dispersion across crops and regions in patterns of variability in crop yields over time, it is important to draw conclusions by evaluating many crop-region combinations. Therefore, an easy to use methodology is needed to draw inferences about yield trends and variabilities. Second, a longer data period (40 years) is preferable to a shorter time period (30 years), especially if the growth pattern in trend yield is erratic.

For the 75 data series evaluated we found frequent occurrences of heteroskedasticity (60%), autocorrelation (47%)

and non constant CV (29-36%). Unexpectedly, we did not find many examples of non- normality (11%). We did find, however, that normality tests based on OLS residuals overestimated non normality by a factor of three.

We argue for and present a battery of tests within the ML framework. This prevents attributing one misspecification for another, and allows one to locate cases of multiple misspecifications. Table 1 gives numbers of cases where pairs of specifications are rejected.

Variability or risk measures needed depend upon the intended audience and purpose. We evaluated one year post-sample standard deviations about trend for the OLS and ML models. Given the frequent occurrence of heteroskedasticity the OLS standard deviations are often much smaller than the ML estimates for many regions and crops (Table 4). The ratio of OLS to ML standard deviations is a measure of the seriousness of the misspecifications that can occur by using OLS to estimate post sample risk. OLS can also overestimate risk as was the case for hay and rice.

The ML approach does not require any more information than OLS, but it can not replace more complete information in estimation of trend and variability of yields. Often times inclusion of information on conditioning information can diminish heteroskedasticity (Yang, et al.). Weather data, irrigation, technology adoption, acreage planted and pest infestation data are very critical in understanding trend and standard deviations of yield. The ML approach improves estimates but can not solve structural and missing variable problems. These are particularly critical in forecasting trends and variabilities. Likewise, spacial aggregation of data can conceal misspecifications that are present and important to individual producers or groups of producers and buyers.

The proposed methodology must be sufficiently tractable that it can be used by applied economists and understood by clientele groups. This is important if the approach is not to end up as a largely ignored academic exercise. Without imposing excess complexity, the proposed procedures which consider heteroskedasticity and autocorrelation provide greater rigor to risk measurement techniques. Furthermore, the proposed nonlinear trends are an improvement over previous studies that have used simplistic specifications such as linear or simple unweighted moving averages (Singh and Byerlee, Anderson and Hazell). Nonetheless, there is room for improvement, particularly through the use of the estimators that flexibly model trends and distributional shapes.

Table 1. NUMBER OF SAMPLES REJECTING TESTS AND PAIRS OF TESTS AT 0.05 LEVEL (75 SAMPLES)[a,b]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	53	48	41	29	27	22	23	5	3	6	16	18	22
(2)		56	39	35	24	20	20	6	4	7	18	17	23
(3)			45	18	26	22	22	6	3	6	18	15	19
(4)				35	15	12	13	3	2	4	6	7	9
(5)					27	22	23	4	2	5	9	8	9
(6)						22	18	4	2	5	8	7	8
(7)							23	4	2	5	8	7	8
(8)								7	2	5	6	4	5
(9)									6	4	2	4	4
(10)										8	5	6	6
(11)											20	11	17
(12)												20	19
(13)													25

[a]Off diagonal elements refer to the number of cases in which a pair of tests was rejected; diagonal entries refer to the number of rejections of the tests listed below.

[b]<u>Test Definitions</u>

1) LR test of $\alpha_1=\alpha_2=\rho=0$
2) Wald test of $\alpha_1=\alpha_2=\rho=0$
3) Wald test of $\alpha_1=\alpha_2=0$
4) Wald test of $\rho=0$
5) Wald test of $\alpha\propto\beta$ (using $\alpha_0\beta_1-\alpha_1\beta_0=\alpha_0\beta_2-\alpha_2\beta_0=0$)
6) Wald test of $\alpha\propto\beta$ (using $\alpha_0\beta_1-\alpha_1\beta_0=\alpha_1\beta_2-\alpha_2\beta_1=0$)
7) Wald test of $\alpha\propto\beta$ (using $\alpha_0\beta_2-\alpha_2\beta_0=\alpha_1\beta_2-\alpha_2\beta_1=0$)
8) Skewness test using ML residuals
9) Kurtosis test using ML residuals
10) Omnibus normality test using ML residuals
11) Skewness test using OLS residuals
12) Kurtosis test using OLS residuals
13) Omnibus normality test using OLS residuals

Table 2. SOURCES OF ESTIMATION PROBLEMS FOR 75 REGION-CROP YIELD CASES 1950-1989 DATA[a]

Sources of Problems	Percent of Cases
Reject homoskedasticity, no autocorrelation, or both	74.67
Reject homoskedasticity	60.0
Reject no autocorrelation	46.67
Reject both	24.0
Non constant coefficient of variation	29.0 - 36.0
Non normality, OLS residuals	33.3
Non normality, ML residuals	10.67

[a]Based on test results shown in Table 1.

Table 3. PATTERNS OF STATISTICAL PROBLEMS IN YIELD MODELS

<u>Heteroskedasticity (60%)</u>[a]

- widely scattered in all regions
- highly concentrated in:

<u>corn</u>	-	7 of 10 regions
<u>barley</u>	-	8 of 8 regions

<u>Autocorrelation (47%)</u>

■ high in:	<u>cotton</u>	-	7 of 7 regions
	<u>sorghum</u>	-	7 of 8 regions
	<u>rice</u>	-	4 of 4 regions
■ low in:	<u>soybeans</u>	-	1 of 8 regions
	<u>oats</u>	-	1 of 9 regions

<u>Non-Constant CV (36%)</u>

- equally scattered across crops
- not present in:

<u>Pacific</u>	-	1 of 8 crops
<u>N. Plains</u>	-	0 of 7 crops

<u>Non-Normality (11%)</u>

- in relatively minor production areas

<u>soybeans</u>	-	S.E. and Appal.
<u>sorghum</u>	-	Delta
<u>hay</u>	-	N.E. and Mt.
<u>oats</u>	-	Pacific
<u>wheat</u>	-	Lake

[a]Percent of cases evaluated that had the indicated problem.

Table 4. AVERAGE END-OF-PERIOD (1990) RATIOS OF RESIDUAL STANDARD DEVIATIONS FROM THE OLS MODEL TO THE ML MODEL

Average By Crop		Average By Region		Overall
Wheat	.67	Pacific	.86	.784
Rice	1.16	N. Plains	.68	
Corn	.65	N. East	1.68	
Oats	.69	Lake	.52	
Barley	.77	C. Belt	.63	
Sorghum	.65	Appl.	.59	
Cotton	.82	S. East	.53	
Soybean	.78	Delta	.73	
Hay	1.06	S. Plains	.95	
		Mountain	.81	

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Appendix: Distribution Theory for Trend Estimators

The loglikelihood for this model, given the normality of the v_t, is

$$\mathcal{L} = \frac{n}{2}\ln(2\pi) - \sum_{t=1}^{n}\ln(x_t'\alpha) + \frac{1}{2}\ln(1-\rho^2) - \frac{1}{2}(1-\rho^2)\left(\frac{e_1}{x_1'\alpha}\right)^2 - \frac{1}{2}\sum_{t=2}^{n}\left(\frac{e_t}{x_t'\alpha} - \rho\frac{e_{t-1}}{x_{t-1}'\alpha}\right)^2.$$

Although there are a number of ways in which the parameters of this model can be estimated, the (asymptotic) distribution theory is most easily established for the maximum likelihood (ML) estimator. This can be obtained by finding the parameters values that set the derivatives of the loglikelihood, called the score function, to zero. The elements of the score function are

$$\frac{\partial\mathcal{L}}{\partial\beta} = (1-\rho^2)\frac{u_1x_1}{(x_1'\alpha)^2} + \sum_{t=2}^{n}\left(\frac{u_t}{x_t'\alpha} - \rho\frac{u_{t-1}}{x_{t-1}'\alpha}\right)\left(\frac{x_t}{x_t'\alpha} - \rho\frac{x_{t-1}}{x_{t-1}'\alpha}\right)$$

$$\frac{\partial\mathcal{L}}{\partial\alpha} = -\sum_{t=1}^{n}\frac{x_t}{x_t'\alpha} + (1-\rho^2)\frac{u_1^2x_1}{(x_1'\alpha)^3} + \sum_{t=2}^{n}\left(\frac{u_t}{x_t'\alpha} - \rho\frac{u_{t-1}}{x_{t-1}'\alpha}\right)\left(\frac{u_tx_t}{(x_t'\alpha)^2} - \rho\frac{u_{t-1}x_{t-1}}{(x_{t-1}'\alpha)^2}\right)$$

and

$$\frac{\partial\mathcal{L}}{\partial\rho} = -\frac{\rho}{1-\rho^2} + \rho\frac{u_1^2}{(x_1'\alpha)^2} + \sum_{t=2}^{n}\left(\frac{u_t}{x_t'\alpha} - \rho\frac{u_{t-1}}{x_{t-1}'\alpha}\right)\frac{u_{t-1}}{x_{t-1}'\alpha}$$

The information matrix for this model is:

$$I(\beta,\alpha,\rho) = \begin{bmatrix} I_{\beta\beta} & 0 & 0 \\ 0 & I_{\alpha\alpha} & \frac{\rho}{1-\rho^2}\left\{\frac{x_1}{x_1'\alpha} + \frac{x_n}{x_n'\alpha}\right\} \\ 0 & \frac{\rho}{1-\rho^2}\left\{\frac{x_1'}{x_1'\alpha} + \frac{x_n'}{x_n'\alpha}\right\} & \frac{n-1}{1-\rho^2} + 2\left(\frac{\rho}{1-\rho^2}\right)^2 \end{bmatrix},$$

where

$$I_{\beta\beta} = (1+\rho^2)\sum_{t=1}^{n} \frac{x_t x_t'}{(x_t'\alpha)^2} - \rho^2\left(\frac{x_1 x_1'}{(x_1'\alpha)^2} + \frac{x_n x_n'}{(x_n'\alpha)^2}\right) - \rho\sum_{t=2}^{n}\left(\frac{x_t x_{t-1}'}{(x_t'\alpha)(x_{t-1}'\alpha)} + \frac{x_{t-1} x_t'}{(x_{t-1}'\alpha)(x_t'\alpha)}\right).$$

and

$$I_{\alpha\alpha} = 2\sum_{t=1}^{n} \frac{x_t x_t'}{(x_t'\alpha)^2} - \frac{\rho^2}{1-\rho^2}\left[\frac{x_1 x_1'}{(x_1'\alpha)^2} + \frac{x_n x_n'}{(x_n'\alpha)^2} + \sum_{t=2}^{n}\left\{\frac{x_t x_{t-1}'}{(x_t'\alpha)(x_{t-1}'\alpha)} + \frac{x_{t-1} x_t'}{(x_{t-1}'\alpha)(x_t'\alpha)}\right\}\right].$$

The covariance of the ML estimator for (α,β,ρ) can be estimated as the inverse of the information matrix.

Technology Adoption Under Uncertainty

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The paper presents a model of divisible technology adoption under output and input price uncertainty. The model analyzes the objective factors and subjective perceptions that affect adoption decisions. A mixed dichotomous-continuous estimation framework is proposed. The application of the empirical model uses data on Texas dairy industry.

The literature on technology adoption under uncertainty can be divided into two broad streams: static models of adoption behavior of individual firms or farms and aggregate adoption models that analyze technology diffusion over time. Feder, Just and Zilberman provide a comprehensive survey of this literature. In this paper we develop a model of an individual producer's decision to adopt a divisible technology in a setting of risk. Factors affecting adoption and the intensity of adoption are explored. The analytical model and its empirical application are framed in the context of bST (bovine somatotropin) adoption. bST, a yield enhancing growth hormone, has been in the center of considerable controversy in the recent years. Though bST provides a natural backdrop for the study, our adoption model is quite general. Applying our model to other divisible innovations requires only minor modifications of variable and parameter definitions.

Since Rogers' pioneering studies, the importance of information gathering and learning-by-doing in the adoption process has been emphasized by a number of analysts including Feder and O'Mara, Stoneman, and, Kislev and Schhori-Bachrach. In tune with these studies we argue that the producer's choices, being based on subjective probabilities associated with the innovation, are significantly affected by his exposure to information about the new technology. In particular, our analysis underscores the 'risk-reducing' role of information - a point emphasized by Hiebert.

The producer's information level also determines whether or not he is aware of the new technology. This has important implications for the empirical analysis. A substantial segment of applied adoption research has used probit or logit analysis on survey data to identify the socio-economic characteristics of adopters (see for example, Jamison and Lau; Lesser et al.; Kinnucan et al; Zepeda). We contend that the estimation results in these studies may suffer from a bias arising from a sample selection problem inherent in the survey data used. To elaborate, observe that the question 'whether or not to adopt' is relevant only to a *sub-sample* of respondents who have heard about the new technology. Consequently, a separate sample selection equation — that explains the binary outcomes of 'heard' versus 'haven't heard' — needs to be estimated. More importantly, awareness about the new technology will be a function of some unobserved attributes of respondents. These attributes may also be influential in the adoption decision. As a result, the errors of the sample selection equation may be correlated with the errors of the adoption equation leading to biased estimates. The empirical framework presented in this study addresses this problem explicitly.

While analytical models in the adoption literature consider degree of adoption to be the relevant choice variable, the underlying assumption in the applied adoption research is that producers allocate resources in an all or nothing fashion between the risk-free technology and a risky innovation. This assumption is evident from the dichotomous dependent variable that characterizes logit or probit adoption models. In this context Feder, Just and Zilberman's comments are revealing:

> "...most adoption research has thus far viewed the adoption decision in dichotomous terms (adoption or non-adoption). But for many types of innovations, the interesting question may be related to the intensity of use (e.g., how much fertilizer is used per hectare or how much land is planted to HYV's). Future studies can rectify this problem by properly accounting for a more varied range of responses and by employing statistical techniques suitable for variables considered." (p. 287-8).

The empirical model proposed in this paper analyzes the 'how much to adopt' decision in conjunction with the 'whether or not to adopt' choice. The model is comprised of three equations with correlated errors: the first two are the sample selection and the adoption versus non-adoption equations, both of which have dichotomous dependent variables. The third equation explains the adoption intensity, a continuous variable. These three estimation equations correspond to the three stages of the adoption process discussed in the analytical model presented below.

I. The Analytical Model

The first phase determines whether or not the farmer has heard about the new technology, bST. The farmer's optimal level of information is a function of information costs as well as individual characteristics such as his education, experience, age, etc. When the acquired information level reaches a threshold value, the farmer "hears" about bST. In the second phase of the adoption process, the farmer decides whether or not to adopt bST. Two types of information play a critical role in this decision: a farmer's knowledge about the current, non-random technology and his subjective assessment about the cost and productivity of the new technology. Adoption is chosen only if the perceived net benefit of the new technology outweighs the opportunity cost of adoption. In the third phase, which need not be temporally separate from the preceding one, the farmer decides what proportion of resources will be allocated to the new technology.

Phase One: Information Collection

It is posited that the farmer's optimal information level is the outcome of an underlying utility maximization characterized by an income-leisure tradeoff. That is,

(1) $$i^*(d) = \arg\max_{i} \left\{ u\left(y(i,d), l(i,d), d\right) \right\}$$

where i^* denotes the optimal information level. Utility is a function of the farmer's income, y, and leisure, *l*. A vector containing relevant economic parameters and the farmer's demographic characteristics is denoted by d. The farmer hears about the new technology if

(2) $\quad i^*(d) \geq i^0$

where i^0 is the threshold information level. The adoption process ends in this phase if $i^*(\cdot) < i^0$. This phase and the one that follows are temporally separate; when the farmer enters the next phase his optimal information level can be viewed as a given parameter in the adoption versus non-adoption decision.

Phase Two: Whether or Not to Adopt

Conditional upon $i^* \geq i^0$, the farmer maximizes the expected utility of random wealth, $\tilde{W}$, through an optimal choice of herd size and adoption level:

(3) $$\underset{x,z}{\text{Max}}\, H = E\left[U\left(\tilde{W}\right)\right] = E\left[U(\tilde{\pi} + I)\right] = E\left[U\left(p(f(x-z) + g(z,\tilde{e})) - w \cdot x - \tilde{r} \cdot z - T(i^*, \cdot) + I\right)\right]$$

subject to $z \leq x$,

where $\tilde{Q} = f(x-z) + g(z,\tilde{e})$, denotes the farmer's stochastic milk production function. Random wealth is the sum of random profit, $\tilde{\pi}$, and an exogenous income, I. x denotes the *total* number of cows in the herd, while z is the number of cows exposed to bST. Traditional milk production technology, $f(\cdot): \Re \to \Re$, is non-stochastic. However, the yield of cows exposed to bST is unknown at this point and this is captured by the stochastic part of the production function, $g(z,\tilde{e}): \Re \times \Re \to \Re$, where $\tilde{e}$ is a random variable. w denotes the variable cost per cow for the entire herd. $\tilde{r}$, in contrast, denotes a unit random cost that is associated only with cows exposed to bST; some examples of bST-specific cost items are injection, special feed, additional management costs, etc. T denotes fixed cost of dairy operations which includes, among other components, the cost of acquired information. In this respect, T can be viewed as the 'sunk-cost' of bST adoption that is borne by the farmer irrespective of whether or not he chooses to adopt. Finally, p denotes the price of milk, which is known to the farmer with certainty.

Assuming, for the moment, strictly interior solutions, the first order conditions of (3) are:

(4a) $H_x(x,z) \equiv E\left[U'(\cdot)\{pf'(x-z)-w\}\right]=0$

(4b) $H_z(x,z) \equiv E\left[U'(\cdot)\{-pf'(x-z)+pg_z(z,\tilde{e})-\tilde{r}\}\right]=0$

where primes and subscripts denote derivatives of functions with single and multiple arguments respectively. Also, let x^* and z^* denote the interior solutions to (3).

Assumption 1 *a:* $g(z=0,\tilde{e})=0 \; \forall \; \tilde{e}$

b: $g_z(z=0,\tilde{e})>0 \; \forall \; \tilde{e}$

Observe that the decision problem in (3) nests non-adoption as a special case, where $z^* = 0$; and, as a consequence of Assumption 1a, when $z^* = 0$, the farmer's wealth is non-stochastic. The following result provides the condition for adoption.

Proposition 1: Let $E\left[g_z(0,\tilde{e})\right] \equiv g_z(0,\bar{e})$ and $E[\tilde{r}] \equiv \bar{r}$. Then, for any positive herd size, x, the sufficient condition for a positive adoption level, i.e., $z^* > 0$, is:

$$g_z(0,\bar{e})-\frac{\bar{r}}{p}>f'(x).$$

The proof of this and all other Propositions in this paper are available in Saha et al. Note, $g_z(0,\bar{e})$ is the bST-induced expected increase in milk production at the margin, while $f'(x^*)$ is the marginal productivity of the traditional milk production process. The result in Proposition 1 accords with intuition. It suggests, adoption will be an optimal choice if the expected marginal net benefit of adoption (LHS of the inequality in Proposition 1) exceeds the opportunity cost of adoption expressed as the marginal decrease in risk-free milk output (RHS of the inequality).

The following proposition summarizes the economic factors that are relevant in the adoption decision when the traditional production technology is concave. These factors follow from the preceding Proposition.

Proposition 2 Dairy farmers

(i) with larger herd size,

(ii) who expect the marginal bST-induced production to be high,

(iii) who expect the unit bST costs to be low, and,

(iv) who receive a higher milk price

are more likely to adopt bST.

The result that larger dairy farmers are likely to adopt bST, is in tune with the empirical findings from other studies on bST and other agricultural innovations (see, for example, Zepeda; Parthasarathy and Prasad; Perrin and Winkelmann; Jamison and Lau). The intuition for this result is as follows. The opportunity cost of adoption is the reduction in the number of cows in the traditional, risk-free production process. Given a strictly concave production technology, the marginal fall in risk-free output – resulting from a decrease in the number of cows in the traditional production – will be lower the larger is the current herd size.

Phase Three: How Much to Adopt

Any meaningful analysis in this phase must rest on the underlying assumption that the inequality in Proposition 1 is satisfied. We also assume that the second order sufficient conditions for (3) are satisfied, that is, the matrix $H_{yy}(y^*)$ is negative definite, where $y^*(\tau) \equiv \{x^*(\tau), z^*(\tau)\}$ is the optimal vector of the two choice variables and τ is the parameter vector associated with (3).

Assumption 2a: $g(z,\tilde{e}) \equiv g(z)\tilde{e} = g(z)\cdot\{\bar{e} + \gamma\cdot\tilde{\varepsilon}_1\}$

2b: $\tilde{r} = \bar{r} + \delta\tilde{\varepsilon}_2$

Assumption 3: $E[\tilde{\varepsilon}_1] = E[\tilde{\varepsilon}_2] = 0$

Assumptions 2 and 3 imply that $\bar{e}$ and $\bar{r}$ are the spread preserving mean parameters for the distributions of $\tilde{e}$ and $\tilde{r}$. Also, γ and δ denote the mean preserving spread parameters, i.e., higher values of these parameters denote higher 'riskiness' of bST yield or price. It is important to recognize at this point that the moments of the distributions of $\tilde{e}$ and $\tilde{r}$ are farmer's subjective perceptions and therefore, are functions of his acquired information level. The explicit functional dependence of the parameters γ, δ, etc., on i^* is suppressed at this stage for notational convenience.

Optimal Responses to Parameter Changes

For the purpose of comparative statics, we assume that the dairy farmer knows the bST-specific per-cow cost with certainty and it is denoted by r. Under the assumption that the farmer exhibits non-increasing absolute risk aversion, the following propositions furnish the relevant comparative static properties of optimal herd size and adoption-level choices:

Proposition 3: *a)* $z^*_{\bar{e}} \equiv x^*_{\bar{e}} > 0.$

b) $z^*_r \equiv x^*_r < 0.$

c) $z^*_T \equiv x^*_T < 0.$

Proposition 4: $z^*_\gamma \equiv x^*_\gamma < 0.$

Proposition 5: $z^*_w < 0$ and $x^*_w < 0$ but $z^*_w \not\equiv x^*_w$.

The results in Proposition (3a) imply that a higher expected bST yield will have identical and positive effects on optimal herd size and adoption level. On the other hand, Proposition (3b) and Proposition 5 suggest that the response to higher bST-specific expected costs or higher per-cow costs will be to reduce the optimal herd size and adoption level. Finally, the results in Proposition 4 imply that higher 'riskiness' of bST yield – as expressed through a mean preserving spread in the distributions of $\tilde{e}$ – will lead to a lower adoption level and a smaller herd size.

The Impact of Information On Farmer's Optimal Choices

To analyze how information affects the farmer's optimal choices, the dependence of his subjective risk perceptions on the knowledge about the technology needs to be made explicit:

Assumption 4: $\gamma = \gamma(i^*)$ such that $\partial\gamma / \partial i^* < 0$.

Assumption 4 captures the negative effect of higher information on the perceived 'riskiness' of yield. This means, the higher is the dairy farmer's acquired information level (which is parametric at this stage) the more accurately will he be able to predict bST induced yield and as a consequence, the lower will be the 'risk' associated with adoption. It is readily verified that assumption 4 implies:

(5) $\partial V(g(\cdot))/\partial i^* < 0.$

where V(·) denotes variance. Since information costs, T(·), and the mean preserving spread parameter γ are both functions of the information level, i*, its effect on adoption intensity is:

$$(6) \qquad \frac{\partial z^*}{\partial i^*} = \frac{\partial z^*}{\partial \gamma}\cdot\frac{\partial \gamma}{\partial i^*} + \frac{\partial z^*}{\partial T}\cdot\frac{\partial T}{\partial i^*}$$

By Assumption 4 and Proposition 4 the first term in the RHS of (6) is positive. This captures the 'risk-reducing' benefit of information. The sign of the second term in (6) depends, in part, on the sign of $\partial T/\partial i^*$. It may be argued that the higher is the farmer's information level – resulting from higher education and experience – the lower is his cost of gathering further information. That is, $\partial T(\cdot)/\partial i^*$ is negative. This, in conjunction with Proposition 3c, imply that the second term in the RHS of (6) is also positive, yielding:

$$(7) \qquad \frac{\partial z^*}{\partial i^*} = \frac{\partial x^*}{\partial i^*} > 0$$

The principal implication of the results in (7) is that, diffusion of technology related information and measures that expedite this diffusion will have a positive effect on the adoption level by reducing the subjective uncertainty associated with the new technology. The foregoing results also suggest that learning-by-doing and experience from prior innovations — both of which will be reflected in a higher level of i* — will enhance adoption intensity and increase the scale of production.

II. The Estimation Model

We saw in the analytical framework of the preceding section that a farmer's decision to treat a portion of his herd with bST (Phase 3) is conditional on having decided to adopt bST (Phase 2), which in turn is conditional upon having heard about bST (Phase 1). The estimation model that captures this decision process is formalized in the following equations:

$$(8a) \qquad Y^P = X^P \cdot \beta^P + \varepsilon^P$$

$$(8b) \qquad Y^A = X^A \cdot \beta^A + \varepsilon^A$$

$$(8c) \qquad Y^H = X^H \cdot \beta^H + \varepsilon^H$$

where:

Y^P = a continuous variable denoting percentage of herd to be treated with bST, i.e., z^*.

$Y^A \equiv$ is a binary variable which equals 1 if the farmer chooses to adopt bST, i.e., $z^* > 0$ and Y^A equals 0 if non-adoption is chosen, i.e., $z^* = 0$.

$Y^H \equiv$ is an indicator variable for having heard about bST, i.e., $Y^H = 1$ if $i^* \geq i^0$ and $Y^H = 0$ if $i^* < i^0$; this follows from (2).

X^P, X^A, and X^H are vectors of explanatory variables. Equation (8) embodies a sample selection model since Y^P and X^P are observed only if $Y^A = 1$ and $Y^H = 1$ while Y^A and X^A are observed only if $Y^H = 1$. We assume that:

$$\{\varepsilon^P, \varepsilon^A, \varepsilon^H\} \text{ is distributed as } TVN(0,0,0,\sigma^2,1,1,\psi^H,\psi^A,\rho),$$

where TVN denotes tri-variate normal, $\psi^H = \mathrm{corr}(\varepsilon^H, \varepsilon^P)$, $\psi^A = \mathrm{corr}(\varepsilon^A, \varepsilon^P)$, and $\rho = \mathrm{corr}(\varepsilon^A, \varepsilon^H)$. Maximization of the following log-likelihood function which follows from the definition of conditional probability, provides the M-L estimates of the parameters β^H, β^A and ρ:

$$\text{(9)} \quad \ln L = \sum_{Y^A=1, Y^H=1} \ln \Phi_2\left[X^H\beta^H, X^A\beta^A, \rho\right] + \sum_{Y^H=1, Y^A=0} \ln \Phi_2\left[X^H\beta^H, -X^A\beta^A, -\rho\right] + \sum_{Y^H=0} \ln \Phi\left[-X^H\beta^H\right]$$

The estimated parameters, $\hat{\beta}^H, \hat{\beta}^A$ and $\hat{\rho}$, are then used in forming the regressors in the augmented 'how much to adopt' equation. This augmented equation, based on the bivariate probit model with selection is:

$$\text{(10)} \quad Y^P = X^P\beta^P + \hat{\lambda}^H\theta^H + \hat{\lambda}^A\theta^A + \eta$$

where:

η is the error term,

$$\hat{\lambda}^H \equiv \phi(W^H)\cdot\Phi\left[\left(W^A - \hat{\rho}X^H\right)/\left(1-\hat{\rho}^2\right)^{1/2}\right]/\Phi_2,$$

$$\hat{\lambda}^A \equiv \phi(W^A)\cdot\Phi\left[\left(W^H - \hat{\rho}X^A\right)/\left(1-\hat{\rho}^2\right)^{1/2}\right]/\Phi_2,$$

$W^H \equiv -X^H\hat{\beta}^H$, $W^A \equiv -X^A\hat{\beta}^A$, and

Φ_2 is the bivariate normal c.d.f $\Phi(W^H, W^A, \hat{\rho})$ whose p.d.f is denoted by ϕ_2.

The coefficients in (10) are estimated by least squares regression of Y^P on $X^P, \hat{\lambda}^H$ and $\hat{\lambda}^A$. The asymptotic-covariance matrix associated with (10) is:

$$V = (X^T X)^{-1}\left[X^T(\sigma^2 I - \pi)X + (\theta^H)^2 X^T G^H \Sigma G^{H^T} X + (\theta^A)^2 X^T G^A \Sigma G^{A^T} X\right](X^T X)^{-1}$$

where: ^{T} denotes transpose,

$$X = \left[X^P : \hat{\lambda}^H : \hat{\lambda}^A\right],$$

$$\pi = \mathrm{diag}(\pi_1, \ldots, \pi_N),$$

$$\pi_i = (\theta^H)^2 W^H \hat{\lambda}^H + (\theta^A)^2 W^A \hat{\lambda}^A + \left(\theta^H \hat{\lambda}^H + \theta^A \lambda^A\right)^2 - \left[2\theta^H \theta^A - \rho\left((\theta^H)^2 + (\theta^A)^2\right)\right] \cdot \phi_2 / \Phi_2,$$

$$\Sigma = \text{asymptotic covariance matrix of } \left[\hat{\beta}^H, \hat{\beta}^A, \hat{\rho}\right],$$

$$G^j = \partial\hat{\lambda}^j \Big/ \partial\left[\hat{\beta}^H, \hat{\beta}^A, \hat{\rho}\right] \quad j = H, A, \text{ and}$$

$$\hat{\sigma}^2 = \left(1/N\right) e^T e - 1/N \sum_{i=1}^{N} \pi_i$$

with e and N being, respectively, the estimated error vector and the number of observations in (10).

An Application: bST Adoption in Texas Dairy Industry

Clearly, the data requirement to estimate the model outlined above is rather onerous; in particular, specific data pertaining to the three phases of the adoption process are required. A data set on the Texas dairy industry provided the closest approximation to our requirements. The data set is based on a telephone survey of Texas dairy farmers undertaken in mid-1992 by the Texas A&M Extension Service and conducted by Public Policy Resources Laboratory. Unfortunately, the data set contained little information on the production costs and other economic characteristics of the dairy farmers. We, nevertheless, present the results of the empirical analysis emphasizing that its main purpose is to show that the empirical model, though complex, can be estimated.

The estimation was done using Limdep, version 6.0. The relevant parameter estimates and the asymptotic t-ratios are presented in Table 1. Since it has been argued in the analytical model that herd size is endogenous, an instrument for the regressor 'herd size' would seem appropriate. However, lack of data on costs and other production characteristics prevented estimation of a separate herd size equation whose predicted values could be effectively used as a suitable instrument.

The estimation results, in the main, concur with predictions from the analytical model. They show that the two most important factors explaining whether or not a farmer has 'heard about bST' are his age and his education level. In the phase 2 regression equation, 'herd size' is positive and significant, a result that substantiates Proposition 2(i). The negative coefficient for 'experience' suggests that younger and less-experienced farmers are more likely to be first adopters. Education level and prior experience in technology adoption have positive effects on adoption decision.

The coefficient estimates in the phase 3 equation are mostly insignificant. This reflects, in part, the lack of data on production and cost variables which are most likely to play an important role in the level of adoption decision. A further problem, inherent in the data set, stems from the *ex-ante* nature of the study. Dairy producers have had no opportunity to learn about the new technology through their own or other farmers' experience. Consequently, their perceptions about the technology's prospects and costs are largely unclear. This ambiguity is reflected in farmers' responses to adoption related questions. The lack of clarity is likely to be most pronounced on the question of degree of adoption and is reflected, in part, in the phase 3 coefficient estimates.

III. Concluding Comments

The paper presented a model of divisible technology adoption under output and input price uncertainty. Farmers optimally chose not only the portion of resources to be devoted to a new technology but also the total amount of resources allocated to the production process. The model attempted to identify the economic characteristics of adopters and to analyze the objective factors as well as subjective perceptions that affect adoption decisions. The analytical findings also underscored the 'risk reducing' role of information and its positive effect on adoption intensity.

A general framework for estimating the decision equations which follow from the paper's analytical structure was presented in the empirical section. It was argued, in early stages of technology diffusion, only a sub-section of producers are aware of the new technology. Consequently, adoption estimation based on survey data may suffer from a non-random sample selection bias since the decision to adopt a new technology is relevant only in the case of survey-respondents who are aware of that technology. The paper's proposed empirical structure explicitly addressed this problem. Further, producer's choices often involve not only the dichotomous choice of whether or not to adopt but also the continuous choice of adoption level. Again, the latter question is relevant only for that sub-sample of producers who have decided to adopt. Thus, the paper's empirical model set out the maximum likelihood function based on relevant conditional probabilities and proposed a mixed dichotomous-continuous estimation framework. The working of the model was illustrated through an application using a data set on Texas dairy farmers. The estimation results provided some intuition into the adoption process and, in the main, provided support for the paper's analytical results.

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Table 1A: Estimation Results

Phase 1: Whether heard about bST	
constant	-1.2439**
	(-2.24)
herd size	0.0005
	(1.28)
age	0.0145**
	(2.36)
education	0.3414***
	(3.77)
ρ	0.9832
	(0.60)
Number of Observations	319

	Phase 2: Whether to Adopt bST	Phase 3: % of herd to be treated with bST
constant	-1.1992**	-74.708
	(-2.08)	(-0.76)
herd size	0.0009**	0.0051
	(2.13)	(0.45)
efficiency	0.0081	0.3694
	(0.87)	(0.51)
experience	-.0120*	0.0345
	(-1.87)	(0.06)
education	0.0988	8.6700
	(1.35)	(1.32)
expand	0.1618	-1.5349
	(1.08)	(-0.12)
prior adoption	0.1865	19.976
	(1.20)	(1.43)
Number of Observations	264	139

Numbers in parentheses are asymptotic t-statistics.

***, **, and * denote significance at the 1%, 5%, and the 10% level respectively.

herd size: number of cows in the producer's herd;
age: the dairy owner's age;
education: number of years of dairy producer's schooling;
efficiency: the average daily milk production per cow;
experience: the dairy producer's number of years of operating experience;
expand: a dummy variable which took a value of 1 if the producer expressed plans of expansion and zero otherwise;
prior adoption: a dummy variable which took a value of 1 if the dairy producer had adopted dairy innovations in the past and zero otherwise.

Pilot Tests of The Group Risk Plan By the Federal Crop Insurance Corporation

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The debate over crop insurance has again intensified. An early version of the President's FY 1994 budget recommended replacing the current crop insurance program with an area-yield plan as it is designed in the Soybean Pilot project. In that project the program is the Group Risk Plan (GRP). (The Area-Yield Plan and the Group Risk Plan are one-in-the-same.) The final version of the President's budget states:

> "...It is proposed that the program be changed to provide coverage on an area-yield basis in most areas. The phase-in of such coverage would begin with the 1994 crop. Individual coverage will be continued in 1994 for programs in counties that have a loss ratio of no more than 1.1 . . . "

Significant questions are unanswered. Many of these questions can only be answered via pilot testing. The Federal Crop Insurance Corporation (FCIC) initiated such a pilot test for soybeans in 1993 and will provide GRP for wheat in selected counties in 1994 crop year. It is proposed that similar test be conducted for more soybean counties, corn, grain sorghum, peanuts, cotton, and barley. There has been much confusion and misinformation regarding GRP. In short, the politics have moved out ahead of the education. This paper presents a number of issues surrounding the Group Risk Plan. The intent is to provide a balanced assessment of the advantages and limitations of GRP.

Policy Issues and GRP

Since The Federal Crop Insurance Act of 1980, there has been tension within the policy process regarding alternatives for U.S. disaster assistance policy. The tension peaked after the 1988 drought as Congress created The Congressional Commission for the Improvement of the FCI Program. Events leading to the 1990 Farm Bill clearly displayed the nature of the problem as the dual problems of high costs and low participation became catch phrases for those working on the issues. Since this time the need for risk management alternatives for U.S. farmers has intensified. If efficiency and equity are major performance criteria then a case can be made for insurance alternatives. "Fixes" have been tried with varying degrees of success. Differences in regions and crops have created new thinking about alternate approaches to providing crop insurance to farmers. The Group Risk Plan can easily be classified as the most dramatic departure from traditional approaches.

The Group Risk Plan is a simple, yet potentially effective risk management alternative. GRP effectiveness can be enhanced with private sector initiatives that offer supplementals. The GRP pays only when county yields drop below a threshold as defined by the FCIC estimated expected county yield and the level of coverage that the farmer purchases.

The idea of insuring farmers based on the risk in the surrounding area is over 40 years old. Professor Halcrow of the University of Illinois first researched this idea for his Ph.D dissertation. In the Canadian Province of Quebec, a program like the Group Risk Plan has been successfully in place since 1977. In 1989, the Crop Insurance Commission recommended a pilot test on the GRP, as did the 1990 Farm Bill.

GRP can provide affordable risk protection that is superior to the current MPCI for some farmers (see Miranda and Hourigan). GRP has a major weakness in that an individual farmer can have a loss and not receive a payment if the county yield is not low. There are three ways to fix this problem: 1) private-sector supplemental products; 2) combined low-level MPCI and GRP; and 3) rezoning so that farmers with similar yields are grouped together (each of these are discussed below).

In many ways, GRP is a compromise between free disaster assistance and the current Multiple Peril Crop Insurance (MPCI). Unlike MPCI, it does not pay based on individual losses. Similar to free disaster assistance, it pays when an area (the county for now) has a loss. Like MPCI, farmers can count on the GRP when there is a widespread-pervasive loss (farmers do not have to wait for Congressional action). Also, like MPCI, the GRP is priced according to relative risk reducing the chances of benefits being bid into land prices or that it will alter production practices in a negative fashion.

However, unlike MPCI, the GRP does not have many problems associated with farm-level crop insurance. Since farmers have no incentives to lose a crop when they are insured under GRP, there should be no excess losses under a sustained GRP program. This cost savings was a major motivation for OMB endorsement. The fundamental problems of adverse selection and moral hazard are major reasons for bad loss experience and low participation in MPCI. GRP is designed to significantly reduce adverse selection and moral hazard. With GRP, farmers no longer know more about the risk of the contract or the probability that they will collect than what FCIC knows. This balance of information should mean that farmers will not choose to participate simply because they know that they are being offered a money-making contract. In short, GRP should be cost effective -- excess losses should not be a long run problem. Timing of sales closing dates may be an issue in some areas as farmers may be able to select the years to purchase GRP based on weather forecast.

The GRP is also appealing because it reduces the administrative cost of Federal crop insurance significantly. Underwriting for coverage would not be needed. Farmers would not have to keep records nor be subjected to the same paper work requirements. This should make the GRP more appealing to farmers. There would be no need for claims adjustments on individual farms. The primary underwriting needs would be when there were questions regarding the level of protection selected by a farmer. Compliance needs would be greatly reduced and rate-making could be simpler and less expensive than the current system.

Providing a subsidy for the GRP above the administrative subsidy will very likely provide every farmer an expected long-term return that is greater than the premium costs. The current program does not do this. Some farmers gain more than others while some farmers cannot expect to get back what they put into premium payments. This factor alone could improve participation significantly compared with MPCI. Since total premiums are likely lower, total cost of the subsidy should also be less under a GRP than for MPCI.

The information needs for this plan are clear -- quality county yield data. Resources will be needed for NASS to improve their ability to estimate county yields. It may be necessary to have resources standing by to make quick assessments when county yields may be below the deductible levels. This would be necessary to provide for timely payments. Further, in some regions of the country, the county is likely an inappropriate unit. If this plan were widely accepted, many procedures used by NASS would have to be reviewed. The most serious problems may be in areas where there is small acreage or only a few farmers in the county who could influence the outcomes. In addition, time tables on the availability of NASS data will need to be moved up so as to make payments at or shortly after harvest.

In summary, GRP has potential to score well on all three components of cost: 1) there should be no excess losses; 2) the administrative cost should be less; and 3) premium subsidies may be lower. These are the reasons OMB was attracted to GRP. There are good reasons not to expand GRP nationally at this time. The primary reasons center on the availability of NASS data and uncertainty as to the degree of risk protection GRP will provide for farmers in some regions. Long series of county NASS data are needed. These data are not available for minor crops and for areas with limited production of major crops. Further, it is important that the educational effort be developed to help growers and lenders understand how to use GRP before rapid expansion.

Besides the very attractive feature of cost effectiveness, GRP can also offer risk management protection for many farmers (Miranda):

* In research that compares the current design of GRP with the current MPCI program, over 60 percent of nearly 3,000 soybean farms would have received superior risk protection from GRP during the 1980s. These data were taken from 10 years of FCIC records for soybean farms (Hourigan).

* Farmers who have never purchased crop insurance should also find GRP attractive. Many of these low-risk farmers have not purchased MPCI because it is priced at levels that exceed their risk. Current mandates to improve the actuarial performance of MPCI will only exacerbate this problem.

* Farmers who are concerned about widespread catastrophic risk will be attracted to GRP. It is relatively inexpensive and it can protect them against events such as drought and hurricanes.

GRP will not work for all farmers. A precondition for GRP is that the farm yield must be correlated to the county yield. For those farmers who farm in a part of the county where soils are different or they are exposed to flooding, GRP will be less effective. Once again, there are ways to fix these problems (see below).

The other problem is that some farmers will receive benefits when they don't have a loss. There are several things to focus on concerning this important problem. First, the event is relatively rare. In the research with 3,000 case farms, this occurred less than 5 percent of the time for the 90 percent coverage level. Second, farmers have paid a premium based on the county yield -- they are entitled to collect. There are a number of contingent markets (e.g., futures options) that have this feature. Finally, the simple fact that farmers can collect when they don't have a loss is fundamental in providing incentives for farmers to continue to try to grow a crop during bad conditions -- moral hazard is eliminated.

Pilot Tests

Soybeans presented a good crop for the first test of GRP. Soybean contracts have presented a serious problem for FCIC during the 1980s. If only seven Southern states would have had a loss ratio of 1.0 on soybeans during the 1980s, FCIC would have had an overall loss ratio of 1.17 instead of 1.56. This alone would have significantly changed the nature of recent debates. Bad experience has also resulted in rate increases and downward adjustments in coverage levels that have all but eliminated participation by soybean growers in several states.

The initial pilot test on soybeans was restricted to well-defined markets. Thirty markets were identified with from 2-6 counties and at least 100,000 acres of soybeans. Besides the Southern states where MPCI has performed poorly, several other states were included because of low participation and problems similar to those in the South. In total, thirteen states were identified. The identified markets represent the type of diversity that is needed to provide the most learning opportunity from a limited pilot test.

At this time, a pilot test for wheat has been approved. There are 175 counties in the wheat test. The criteria for selection was a bit different in the wheat pilot. Counties with large expected losses were selected. In part, this was done to help alleviate anticipated problems as FCIC modifies the current MPCI program.

It is likely that FCIC will expand pilot testing of GRP into five other crops: 1) corn; 2) grain sorghum; 3) cotton; 4) barley; and 5) peanuts. When soybeans and wheat are added, these crops are the major U.S. crops in terms of planted acres (240 million). These seven crops are clearly dominant for crop insurance as they accounted for $600 million dollars of the total FCIC premium in 1992 and 75 million insured acres. This is roughly three-fourths of FCICs total business.

Risk Management Issues for the GRP Index

When growers understand that county yields are used to establish the payment for GRP, the next questions should focus on the history of those yields. To the extent that GRP does not change the procedures used by NASS to develop county yields (and it should not at this point), then that history is useful information for growers who are trying to protect their farm income. If farmers can compare their yield history to the history of payments that they would have received with various GRP policies, they will have a better understanding of how well GRP may help offset losses. When farm crop losses match GRP payments then GRP can offset lower incomes due to crop failure.

We have learned that farmers understand that the GRP is an index that can protect more than potential soybean shortfalls. A farmer who examines the history of payouts under GRP may find that GRP paid when his soybean yields were not that low. However, in reflecting on the farm operation for that year, he may also realize that, due to the rotation pattern for that year, soybeans were in the low land and corn was on the high ground. If this is the case and the GRP payments are due to dry conditions, then it is likely that the farmer needed some compensation to offset corn losses. It may also be that the farmer uses irrigation for soybeans. If this is the case, soybean yields may be okay in a year that the soybean GRP pays. However, if the GRP payment is due to dry conditions, irrigation costs are very likely high. A GRP payment may be needed to offset the high irrigation cost.

To summarize, the GRP index can protect farmers from a variety of risks other than those associated with a crop shortfall for the GRP crop. Farmers recognize that GRP payments are only going to be made when bad weather events have created serious losses in the area. When this occurs, the odds are high that individual farms within that county also have losses due to those bad weather events. In short, GRP can protect against crop losses for other crops besides the GRP crop; GRP can protect against increased cost of production due to farm management strategies (e.g., irrigation) that are used to offset crop losses; and GRP can protect against livestock losses due to stress that may be created due to adverse weather. Growers need to discover the relationship between historic GRP payments and their farm income to fully appreciate the degree of risk protection offered by the GRP index.

Considerations for Fixing the Problem of Individual Protection

Despite the potential whole-farm protection that may be offered by GRP, it may be useful to provide farmers some type of protection for individual losses. Everyone has been careful in pointing out that the biggest shortcoming of GRP is that an individual farmer can have a loss when the county yield does not trigger a GRP payment. Possibly the biggest reason to be concerned about this issue is that creditors may be reluctant to allow farmers to use GRP as collateral in production loans. There are three possible ways to minimize this problem: 1) combine a low level of MPCI coverage with GRP as a combined Federal product; 2) begin the process of developing geographic zones with homogeneous soils and climates instead of using county boundaries; and 3) encourage private sector development of companion products;

A Combined Federal Product

One solution is to package a level one (50 percent coverage) with GRP. Actuarial performance of level one coverage has been much better than level two or three. In most areas, loss ratios for level one coverage are below one. The advantage of selling level one coverage with GRP is that there would be some minimum protection should a grower have a near total loss when the county does not suffer a loss or when the county loss is very low. Additionally, this policy could replace the need for making an early payment on GRP since any losses below 50 percent would be paid earlier than GRP payments.

Several objectives should be in place for such a combination: 1) the level one coverage should be simple; 2) the package should be affordable; and 3) opportunities for double payments should be low. A simple 4 year APH may be the best alternative for establishing yield coverage for the level one portion of this package. However, given all of the battles over APH and establishing yield levels, a return to area-yield may work for these purposes. To make the package affordable new considerations for rating may be in order. For example, the catastrophic load (cat load) in the GRP may replace the need to cat load the level one coverage. Finally, it should be possible to reduce the combined payments to control overpayments. A concern would be adverse selection in that farmers who had yields that did not track the county yield would be more attracted to the combined policy.

Alternative 1

Level one coverage could be sold with GRP allowing for early payments when the grower had a loss below 50 percent. Again, this may replace the need for a preliminary GRP payment. If the grower receives a level one payment, the payment would be deducted from any GRP payment that is due in the spring. Since the GRP has a cat load, the cat load for the level one policy could be removed. If this were done, there may be no need to subsidize the level one coverage since the GRP subsidy would remain. A combined package of GRP at 90 percent with GRP protection levels lower than the maximum could be quite affordable.

Alternative 2

This combined GRP and level one package would work much the same except the payments would be handled differently. Combined payments would be capped at twice the protection level provided by the level one policy. The advantage of this alternative over number 1 is that it would provide more protection. Since county yields should never go to zero, growers would still have incentives to purchase high GRP protection levels. The disadvantage is that both rates would need a cat load making the policy more expensive. The other concern is that once you cap the payments based on the coverage yield you have increased the importance of that number. This opens a whole set of issues about APH/etc. that make this alternative less attractive.

Rezoning by NASS

Another important aspect of the GRP is that county boundaries are political. In larger counties it is unlikely that the county is homogeneous in soils and climate. In other countries that have used this type of insurance, the most dynamic aspects of the program is a continual redrawing of zone boundaries. Zones represent the area used to establish the loss bases. Zones are to reflect a homogeneous production area. In Quebec, an average size zone appears to include between 300 and 400 square miles. The average size county in the lake states is around 500 square miles. The Farmer's Union in Quebec has been active in helping change zone boundaries as farmers learned what zone their farm should be in. Zones are different for different crops.

It is possible to begin a similar rezoning process in the U.S. This would require several pieces. First, priority should be given to regions that have the largest counties and/or to regions that have risk that are clearly not widespread (i.e., where major cause of loss is from a spot loss event). In both cases the intend is to focus limited resources where they have the potential to do the most good.

A good starting place for rezoning is FCIC's old area maps that were used when coverage levels were established based on the section of the county where the farm was located. These maps should still be around as this program was in place as recently as ten years ago. Once the zones are established the trick would be to develop coverage and rates. There may be some methods for allocating NASS yields to the zones. It may be that plant growth simulation models could contribute (e.g., SCS uses EPIC) to these efforts. Much of the process for setting initial rates and coverage would be based on good judgment. Both rates and coverage could be changed over time. I am not sure how the Canadians phased in their zone program. It may be worth sometime to investigate this point as the Quebec program had to deal with these questions in 1977.

Encourage Private Sector Development of Companion Products

A more volatile issue regarding the Group Risk Plan (GRP) is the question of what delivery system is appropriate. Many reinsured companies have been concerned that the GRP could be delivered by the public sector. Given the current concerns over the budget cost of the Federal Crop Insurance program, policy makers may decide that public sector delivery could be less costly to taxpayers. The strongest argument for private sector delivery is the need for supplemental products that can be coupled with the GRP. Private company selling of GRP will enhance introduction of private supplemental products. It is also probable that private initiatives will evolve to offer tailored products for the region and crop that would backstop GRP. The major weakness of GRP is that an individual farmer can have a loss when there is no GRP payment. Private companies can put products with GRP to remove this weakness. Consequently, private companies should be allowed to sell GRP and develop and market other forms of insurance to supplement GRP.

Some Issues Regarding Private Sector Delivery of MPCI

Private sector delivery of Multiple Peril Crop Insurance (MPCI) has been moderately successful. Many growers and bankers like the private sector delivery. Sales agents should be more inclined to service a contract. Private agents have greater incentives to market and sell than a government agent would. Private companies should have incentives and opportunities to tailor products. Over 90 percent of all MPCI is sold and serviced by private reinsured companies. Many argue that allowing private sector delivery of MPCI was important to development of private sector supplemental insurance products. These add-on products are designed to cover special risk that may not be covered by the MPCI contract. Although there are several supplemental products offered by the private companies, the rate of their development has been slow. There are several reasons for this. The most significant reason is that any private product that is sold with government subsidized MPCI must be neutral in the risk effects on MPCI. In short, it would be inappropriate for a private company to sell a supplemental product that was coupled with MPCI in such a fashion that the risk of the MPCI product would increase. The approval process has been a constraint for introduction of supplementals. Many of these issues would not be important for add-on products that would be coupled with GRP. GRP is designed so that individual farmers cannot influence payments.

Besides questions about risk associated with new products, there are questions about how the delivery system has increased the risk of MPCI. Does allowing private sector delivery increase the risk of MPCI? The sales agents have incentives to sell. They have very little incentive to be concerned with the risk of the MPCI contracts they write. As companies do share the risk, they have incentives to underwrite sales activity by agents.

Among the most serious problems of MPCI is adverse selection. Adverse selection occurs when the high-risk growers do not have to pay premiums that are consistent with the risk they face. Lower risk growers may decide not to purchase because premiums are too high for their farm-yield risk. When a grower knows that the yield offer is better than he or she can expect to produce, they will buy MPCI. These growers have a higher probability of loss. Given the current structure of the Actual Production History (APH) for establishing yield offers, it is easy to understand how sales agents become directly involved in exacerbating these problems. The APH offer is designed to be the simple average of ten years of proven yields. Since few growers have ten years of records, a Transitional or T-yield has been used. In addition, growers have some flexibility in defining insurable units (they can subdivide different farms they are farming). To make a sale, agents have every incentive to work with the numbers to decide what mixture of actual yields, units, and T-yields provides the maximum yield offers. This reality should not be taken as an indictment of private sector delivery. Public sector sales agents would have many of the same incentives given the current rules.

Private MPCI products that would be sold with GRP would still have the potential for adverse selection. However, the incentives for fixing these problems would be with the private companies that contract with the agents. These incentives would very likely lead to a different system that would place more responsibility with agents.

Many questions regarding shared risk between the private reinsured companies and the government center on the structure of the reinsurance agreement. Companies can identify high risk farmers and place them in a high risk pool. The government then shares nearly all of the risk for this set of growers. Risk-sharing is essential for private sector involvement. Multiple Peril Crop Insurance is a risky proposition for private sector companies because of the highly correlated losses that can occur due to widespread events such as the 1988 drought in the Mid-west. The international reinsurance sector does not have the capacity to cover these types of risk. If MPCI were more actuarially sound, GRP could serve as reinsurance as well as a facilitator of reinsurance from international markets.

Private Sector Initiatives

Private sector efforts to insure the individual when the county does not have a loss can be important for effective risk management under GRP. For growers who have yields that do not track well with county yields this is even more important. In areas where hail is a major cause of loss, private hail insurance is an excellent example. Major thunder storms that have hail would increase the odds of a hail loss and decrease the odds of drought losses. Therefore, it is likely that farmers can suffer a hail loss when the county yield is high. Hail insurance will very likely have higher losses when there is no GRP payment. In others words, hail insurance should be highly complementary with GRP. This is particularly true if most county losses are due to drought.

There is an argument that GRP may substitute for reinsurance. A major justification for government involvement with MPCI is that there is market failure -- the private sector is not able to take the widespread and correlated risk associated with MPCI because of the difficulty in building adequate reserves to cover large losses. GRP protects against widespread and correlated risk by offering insurance based on what happens to yields in the county. There is some concern among private companies that GRP may not offer enough protection to substitute for or facilitate private reinsurance activity. Part of that discussion is likely influenced by the very conservative position that private reinsures are taking due to recent heavy losses in the U.S. and around the world. To address some of these concerns, it may be necessary to offer GRP at 95 percent of the expected county yields.

To fix the problem of farm losses when GRP does not pay, a private product could be structured so that low levels of coverage could be sold with GRP. This would also simplify early payments when the grower had a loss. If the grower receives a payment, the payment would be deducted from any GRP payment that is due in the spring. Since the GRP has a cat load, the cat load for the private MPCI policy could be removed. A combined package of private MPCI and GRP could be quite affordable. The company could have first claim to the GRP payment. They would structure their own private MPCI policy that would make the timely payment. Companies would pay the grower any excess funds when the GRP payment is greater than the private MPCI payment.

The real advantage of a combined GRP/Private MPCI is that it places the burden for fixing MPCI problems where it belongs -- with the private sector. This combination would mean that companies could begin new rating in areas where the current problem is beyond fixing. FCIC will never be able to reduce rates in areas with bad loss experience. Private companies could do this with a private MPCI product. They would simply set their own rates and their own underwriting standards. Further, unlike a Federal product, companies could set different coverage levels based on the risk in the region (i.e., it would be unlikely that Congress would allow FCIC to differentiate the deductible based on relative risk).

Companies would have much more freedom to fix the problems that they have been concerned with. Companies could use economics to establish charges for administrative costs. Companies could be innovative in making the combination work. Only certain perils may be covered in an MPCI policy (e.g., drought, freeze, excess moisture). In short, I believe that the opportunities are very good. There are those who argue that farmers will not buy a private MPCI policy that is not subsidized. If this is true, then that is a market decision and those growers should consider other forms of risk protection (in some areas this may mean less risky enterprises like livestock). Further, with a GRP that has a cat load, it is likely that the add-on MPCI could be affordable.

For sometime, there has been a search for the proper mixture between private and public involvement in risk sharing for crop losses. GRP has the potential for improving this mixture. GRP is well-designed for those who believe an appropriate role of government is to handle pervasive and widespread losses. GRP leaves individuals at risk when they have isolated losses. Many would argue that government should not be involved in fixing the problems associated with isolated losses. GRP can facilitate private sector initiatives that will handle isolated losses. Private companies need to have the opportunity to sell GRP to make that happen.

APPENDIX A -- Some Basic Questions About GRP[1]

How does GRP work?

When the county crop yield is low in any given year, most farmers in that county will have low yields. Farmers who purchase GRP will be paid whenever the county yield drops below a specified level. Planted acreage yields will be used to account for very bad years when some acres may not be harvested. Payment rates -- which will be based on the percent of lost county yield below the threshold and the chosen trigger yield -- will be the same for all farmers who purchase the same contract. Farmers can select a desired trigger yield and amount of protection per acre.

Why does FCIC allow for liabilities that exceed the expected county revenue?

Some farmers will have yields above the county average expected yield. It would be unfair to restrict the protection these farmers can select to the average expected county revenue, since their expected revenue will be above that level.

In addition, since farm level yields and county yields do not move up and down together perfectly, selecting a higher protection can provide more risk protection than limiting the protection to the expected county revenue.

Finally, the probability of very low yields for individual farms is higher than the probability of very low county yields. Therefore, even though FCIC will allow for protection to exceed the expected county revenue, a payout at the maximum protection would be extremely rare. In the soybean counties, the probability that county yields will be below 35 percent of the expected value ranges from 1 to 7 percent.

How much does GRP cost?

The cost decreases if farmers select any combination of a lower amount of protection and lower trigger yields. Farmers in counties with higher yield risk will also pay more than farmers in counties with lower risk. Even for a high trigger yield, GRP will generally be less costly than the current MPCI.

Calculation of premiums is simple. Rate tables for each county have the rate per $100 of protection for each trigger yield.

Premium = Premium rate x Protection purchased x .01 x acres

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[1]This material was taken from extension education material developed for GRP. If you would like a copy of the complete material call Jerry Skees at (606) 257-7262.

How are payments made?

In order to provide maximum protection, GRP is designed to pay 100 percent of the selected protection in the unlikely event of a zero county yield. If the expected county soybean yield is 30 bushels, farmers may choose a 90-percent coverage level. This means that any time the county yield drops below 27 bushels, farmers who purchased a 90-percent coverage level GRP would receive a payment.

Twenty-seven bushels is derived from the 30-bushel expected yield times the 90-percent coverage level: 30 x .90 = 27. This is the trigger yield. The payment would be based on the percent shortfall from the trigger yield that farmers purchase.

For example, if the county yield is 20 bushels, this is a 25.9-percent shortfall (27 - 20) / 27. Farmers who selected a policy with the $225 protection per acre described above would receive a GRP payment of .259 x $225 = $58.28. Other farmers who purchased GRP with an 80-percent coverage level would receive $37.58 for every insured acre:

Trigger yield = 30 x .80 = 24
Shortfall = (24-20)/24 = .167
Payment = .167 x $225 = $37.58

Again, in the unlikely event that the county yield equals zero, both sets of farmers would receive $225.

Shortfall = (27-0)/ 27 = 1.00 .... as does (24-0)/24
Payment = 1.00 x $225 = $225 for both farmers

GRP payments are based on USDA county yield estimates per planted acre. To make timely payments, there may be a partial payment in December based on early yield estimates.

The 27 bushel trigger yield is multiplied by 95 percent to establish the preliminary payment. Payments may be made when the preliminary yield drops below 25.7 bushels (.95 x 27). This is used to develop the preliminary payment factor.

$$\text{Preliminary Payment Factor} = \frac{\text{95\% Trigger Yield - Preliminary Payment Yield}}{\text{95\% Trigger Yield}}$$

For example, if the crop reporting district yield estimated in November is 20 bushels, the preliminary payment yield is 25.7 bushels:

$$\frac{(25.7 - 20)}{25.7} = .220$$

The payment farmers would receive is:

Preliminary payment factor x Selected protection per acre x .67

Under these circumstances, the preliminary payment would be:

$$.220 \times \$225 \times .67 = \$33.17 \text{ per acre}$$

The amount of the preliminary payment must be greater than 5 percent of the selected protection. When the protection is $225, the minimum preliminary payment would be 5 percent of the selected protection of $225, or $11.25 per acre:

$$.05 \times \$225 = \$11.25 \text{ per acre}$$

The 5-percent minimum preliminary payment assures that the value of the preliminary payment is large enough to cover the cost of issuing checks and to limit the chance of overpayments.

Final Payment

In May of the following year, NASS will issue its final report on actual county yields. This number will be used as the **final payment yield**, which will be used to calculate the final payment:

$$\text{Final Payment Factor} = \frac{\text{Trigger Yield - Final Payment Yield}}{\text{Trigger Yield}}$$

Final Payment = Final Payment Factor x Protection Per Acre x Acres - Preliminary Payment

For this example, let's assume that the preliminary payment yield matches the final payment yield. The NASS county yield issued in May is 20 bushels per acre. This is a 25.9-percent shortfall from the trigger yield of 27 bushels.

$$\frac{(27\text{-}20)}{27} = .259 \qquad \text{(Final Payment Factor)}$$

The payment farmers would receive is based on the percent shortfall from the trigger yield and their maximum protection per acre. Under these circumstances, the payment is:

$$.259 \times \$225 = \$58.28 \text{ per acre}$$

But the farmers with this coverage level received a preliminary payment of $33.17 per acre in December. Shortly after NASS releases its final yield figures in May, farmers will receive their final payment:

$$\$58.28 - \$33.17 = \$25.11 \text{ per acre.}$$

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To Be Or Not To Be: A Regional Project Or An IEG?

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Background

In March, 1992, the participants in the annual meeting of Regional Project S-232 (Quantifying Long Run Agricultural Risks and Evaluating Farmer Responses to Risk) opened discussion on the format alternatives for continuing the productive research collaboration which was initiated over 15 years ago. Discussion centered around the pros and cons of initiating a new regional project versus developing an information exchange group (IEG) for researchers interested in risk analysis. A similar debate did occur during the transition from S-180 (An Economic Analysis of Risk Management Strategies for Agricultural Production Firms) to S-232 when the majority of the participants supported the continuation of the regional project format.

A subcommittee was appointed to survey the profession regarding its interest in participating in an IEG. All participants in S-180 and S-232 were mailed a short questionnaire during the summer of 1992. An announcement of the ongoing survey and an invitation to participate in the survey also was printed in the AAEA Newsletter. Thirty-four individuals completed at least one question of the questionnaire (See the attached list of respondents). The respondents' prior involvement in risk-related regional projects is distributed as follows:

Project	Number/Percentage
W-149 + S-180	2/6
W-149 + S-232	1/3
W-149 + S-180 + S-232	4/12
S-180 only	2/6
S-232 only	5/15
S-180 + S-232	16/47
No previous involvement	4/11
Total	34/100

Nearly three quarters of all respondents were economists who are currently participating in S-232. Most of these individuals have been involved in risk-related regional projects for at least 10 years. These 26 respondents represent 50% of the economists who have been active in S-232. Only four individuals in the AAEA without a prior involvement in the regional risk projects expressed an interest in an IEG by requesting and returning the questionnaire.

Survey Results

The respondents were asked which collaborative format they preferred for collaboration: a regional project or an IEG. Approximately 73% of the respondents preferred the IEG, 18% (6 respondents) preferred a regional project, and three individuals (9%) were indifferent between the two formats. When the opened-ended question was asked as to why an IEG was preferable the respondents listed reasons that fall into two major categories. First, they felt an IEG provided more flexibility in subject matter content and format. Specifically, concerns were expressed about the rigidity of a regional project, the recent experience with being "forced by administrators" to work on a problem which they defined, the need to focus on research objectives "mandated" by a committee, and the pressure to produce a group product (e.g. a regional publication). A second major category of concerns fell under the heading of "more open exchange of ideas and information on recent developments". It is clear that many participants prefer the "old format" which emphasized paper presentations and discussion, with less emphasis on subcommittee meetings.

Those respondents who prefer a regional project felt that it would be easier under this structured format to obtain research and travel funds. Several individuals felt that more serious research would be completed under a regional project, whereas an IEG might "degenerate into just a paper presentation session". They liked the less flexible format of a regional project because it was a proven mechanism for generating research results.

All respondents were asked to list what they thought were the disadvantages of an IEG. As noted in the previous paragraph, 12 of the 26 individuals responding to this question felt that the lack or uncertainty of funding for an IEG would be a problem. Other concerns surrounding an IEG included the lack of leadership, the tendency of the IEG to lose its focus, and the lack of professional recognition associated with an IEG, especially in the minds of experiment station directors and department heads.

Respondents were asked to frame an argument for administrators in support of their involvement in an IEG. Over half (54%) of the researchers would structure their case around the importance of interaction with their peers which would keep them up-to-date on recent methodological developments and provide a forum for discussion and criticism. Others would argue that their involvement would increase their own research productivity, and in some cases, this would occur at no expense to administrators since all travel would be funded out of grants and contracts. One respondent argued that an IEG would be an efficient (in a cost sense) means for keeping current on developments in risk analysis.

The respondents were asked to vote for two IEG topics or write in a topic which was of specific interest. The results are:

Topic	Number/Percent
The impact of institutional risk on comparative advantage in U.S. agriculture	6/8
Farm-level risk modeling of natural resource issues	18/22
The behavioral foundations of decision-making under uncertainty and applications to agriculture	16/20
Modeling risk response by agricultural producers to emerging environmental regulations	19/24
Trade liberalization, risk, and U.S. farming	4/5
Interaction between crop and livestock risk	6/8
Other topics	11/14
Food safety (2)	
Risk and rural development	
Firm-level risk management modeling	
Non-market valuation techniques/applications	
EPA's approach to environmental regulation and monitoring	
Environmental and health risk	
Uncertainty associated with climate change	
Farm-level risk modeling of national agricultural policy (farm programs) changes with private alternatives	
Strategic decision analysis and related risk	
Impact of risk and uncertainty on the capital and investment requirements of proprietary firms	
Total	80/100

These results indicate that there is interest in continuing the tradition of farm-level modeling. A significant number of respondents are interested in incorporating environmental and natural resource decision variables, constraints, etc. into this research effort. Also, strong interest in the economic theory and tools associated with risk and uncertainty continues among the respondents.

Finally, a series of questions were asked concerning the future financial support for an IEG. The results illustrate the degree of uncertainty surrounding the probable involvement of the respondents.

Question	Percent Response		
	yes	no	maybe
Would your department financially support your involvement in an IEG?	50	10	40
If you answered "no" or "maybe" to the previous question, would you be willing to spend your grant/contract funds to attend IEG meetings?	31	0	69
If you were involved in an IEG, would departmental funds be available for funding a research assistant, in-state travel costs and operations in support of risk research?	24	38	38

These responses indicate that of the 34 respondents, perhaps 22 economists would be willing and able to participate in an IEG which met their professional needs. There could be greater participation, but continued uncertainty surrounding future financial support constrains our "upperbound" prediction. A conservative lower bound guess for future involvement is 15 individuals.

Concluding Remarks

There appears to be a strong interest among the respondents for pursuing the development of an IEG as opposed to a regional project. Increased flexibility and control over the content and format of a valuable information exchange process appeals to most of the participants. Generally, it is recognized that the availability of funds will be a source of uncertainty for either an IEG or a regional project. An area of research interest which appears to be gaining support is farm-level modeling of environmental and natural resource issues. Of course, this topic lends itself to an IEG or another regional project depending on the interests and desires of evolving research coalitions of economists.