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Econometric Analysis of Production Decisions with Government Intervention: The Case of the California Field Crops

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CALIFORNIA AGRICULTURAL EXPERIMENT STATION

Government field crop commodity programs have become increasingly expensive in recent years. Hence, a determination of both the direct effects on the crops controlled by the programs and the indirect effects on competing crops is of evident importance. Accordingly, the major objectives of this study include both the development and the application of a model for the quantitative analysis of government program impact on the supply response of a large set of competing crops.

Since one of the primary goals of government farm policy is the stabilization of farm prices and income, any econometric model to be used in the analysis of government program impact on supply response must surely include the possibility of response to changing risk. Accordingly, by employing decision theory and the economic theory of risk bearing, the first part of this study deals with the development of an econometric model for production decisions in an economic environment of changing risk. Although the model was developed for the specific purpose of application in the field crop sector, it is presented in a general framework and is possibly applicable in a much broader class of problems.

In the second part of the study, the model is extended to include the possibilities of response to the various forms of government intervention which describe the field crop programs administered in recent years. Since the resulting model is somewhat more complex than commonly employed econometric models, an estimation technique had also to be derived.

Finally, the results of the application of the model to the analysis of acreage decisions in the California field crop sector are presented. Implications are that acreages of crops regulated by marketing quotas as well as by allotments have been highly influenced by the programs. Crops with voluntary allotments tend to be influenced more by other factors of economic importance as well as by marketing quotas established for other crops. Apparently, the role of risk is more significant in many of the cases where acreage restrictions have not been of a strict nature through most of the period of investigation. Also, since risk seems to have been greatly reduced for most crops with the establishment of allotments, results indicate that increases in acreage may possibly be a direct result of some of the voluntary programs.

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A supplement to this report, containing Appendix A (The Response of Yield), Appendix B (Problems Encountered With the Standard Nerlovian Model), Appendix C (Data Used in the Econometric Analysis), Appendix D (On the Significance of Results in Regression), and Appendix E (Spectral Implications of the Estimated Disturbance Process), can be obtained from the Giannini Foundation of Agricultural Economics, 207 Giannini Hall, University of California, Berkeley, 94720.

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1 INTRODUCTION[1]

CALIFORNIA'S FIELD CROPS SECTOR has been of great importance to the nation as well as to the state. California has led the nation in the production of some field crops and is one of three or four major producing states of several others. During the 1960–1964 period, California ranked first in sugar beets, hay, and barley production; third in cotton lint and cottonseed production; and fourth in the production of rice and grain sorghum (Parsons and McCorkle, 1969). Little has changed since; California hay production now ranks second nationally, while barley has slipped to third (U.S. Statistical Reporting Service, 1971, and California Crop and Livestock Reporting Service, 1971*c*).

California is not only one of the most important field crop-producing states in the nation but also accounts for one of the largest expenditures of public funds on field crop commodity programs. In 1970 more than $120 million of the $885 million in field crop value to farmers was matched by federal funds in the form of price-support and diversion payments (table 1). Nearly 40 per cent of California cotton farmers' income came directly from federal sources. With the programs' high costs, it is only fitting that studies such as this should be concerned with the evaluation of the impacts of government programs.

The major objectives of this study are twofold. First, a more general econometric model of changing expectations incorporating the results of past experience in decision-makers' subjective evaluation of risk is sought; and, second, a quantitative evaluation of the impact of various government commodity programs, including both income-sustaining and price-stabilizing effects on California field crop supply response, is desired. The field crop sector in California is exceedingly complex as virtually every major field crop is produced in sizable quantities. Accordingly, the greater part of this study will be devoted to the development of an econometric model that attempts to reflect adequately all of the major operative forces.

Since there are interdependencies of supply among so many field crops and because so many forces are important in the supply of each crop, particularly those regulated by government programs, great care must be taken in the derivation of the econometric supply-response model. As much simplification as is theoretically justifiable must be employed, so that the resulting model can include all important interdependencies while still being statistically amenable to estimation (given data limitations). Indeed, much work has been done on the adequate representation of dynamic agricultural supply forces in simple response models, the most noted of which is that of Nerlove (1958*b* and 1958*c*). Most of the work, however, has been

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TABLE 1
VALUE OF CALIFORNIA FIELD CROPS AND PUBLIC COSTS OF GOVERNMENT PROGRAMS, 1970

Crop	Acreage harvested	Production	Value	Program costs*
			dollars	
Barley	1,188,000	61,776,000 (bushels)	69,807,000	10,366,087
Sorghum (for grain)	396,000	29,304,000 (bushels)	41,905,000	
Corn (for grain)	216,000	21,168,000 (bushels)	33,445,000	
Alfalfa hay	1,152,000	6,451,000 (tons)	196,756,000	—
Cotton lint	662,400	1,165,500 (bales)	145,726,000	89,763,872
Cottonseed		501,000 (tons)	33,567,000	
Sugar beets	320,800	7,860,000 (tons)	117,114,000	14,438,087
Rice	331,000	18,205,000 (cwt.)	89,205,000	—
Wheat	535,000	22,175,000 (bushels)	30,350,000	6,067,679
Dry beans	174,000	2,666,000 (cwt.)	29,326,000	—
Grain hay	463,000	833,000 (tons)	22,491,000	—
Other hay	292,000	490,000 (tons)	10,086,000	—
Oats	101,000	5,050,000 (bushels)	3,889,000	—
Hops	1,400	2,184,000 (lbs.)	1,289,000	—
Flaxseed	2,000	78,000 (bushels)	242,000	—
Total field crops	6,297,800	20,747,000 (tons)	885,895,000	120,635,725

*Program costs include only direct price support or diversion payments to producers; administrative, storage, and other costs are excluded. Dashes indicate no programs administered or no payments made to producers. SOURCE: California Crop and Livestock Reporting Service (1970), U.S. Department of Agriculture (1970), and private communications with the California Agricultural Stabilization and Conservation Service Office.

directed toward dynamic models in which lags in economic behavior are induced by technological or institutional factors. Methods have been developed for the estimation of almost any conceivable temporal distribution of lags and, of course, the appropriate one for any specific problem can only be determined through a thorough study of the particular industry. A more generally applicable class of models, but one that has been developed much less, is based on a changing subjective knowledge of the economic environment in which the decision-maker operates. Only a few simple models dealing with the first moments of the distributions of relevant variables have been considered on any kind of general basis, and the most popular of these is Cagan's (1956) adaptive expectations model. Second moments generally have been included only in a completely arbitrary way. However, since risk is generally felt to play an important role in farm managers' decisions in California where so many cropping alternatives are available (Carter and Dean, 1960), the development of a more general model of changing subjective knowledge is of utmost importance in the present analysis. Such a model can then be combined with previously used models when technological or institutional considerations demand it.

In the first part of the study, decision theory is employed to examine decision-making behavior in a free market under a broad range of objective functions. Assuming a Markovian economic environment in which the farm decision-makers cannot observe the true state of the environment without error, the appropriate temporal relationship between information and decision variables is developed. Although some specific assumptions are made with respect to decision-makers' subjective distributional families, the resulting econometric model can possibly find general applicability as the distributional families are quite rich and should provide adequate approximations in most cases. Due to the highly technical nature of the underlying decision-theoretic developments in Section 2, the less technically-oriented reader is advised to skip directly from the first paragraph of Section 2 to the last paragraph heading in

Section 2 which provides a short intuitive justification of the free-market decision model.

The second part of the study is concerned with modifications in decision-making behavior brought about by government intervention in the form of price-supporting activities and acreage control. The econometric model is then appropriately extended to include possibilities of various forms of government programs; and, finally, several methods of estimation for the resulting model are discussed and the properties of the estimators are investigated. Again, the less technically-oriented reader interested only in the government program methodology or the empirical conclusions of the study may wish to skip the development of estimation methods in Section 4 or at least the investigation of their properties.

The last part of the study deals with the application of the model to the analysis of supply response in the California field crop sector. The appropriate information and decision variables are first chosen on the basis of a short descriptive study of the organizational aspects of the sector. After an examination of problems of aggregation over decision-makers, acreage response equations are estimated for the eight most important California field crops in each of six exhaustive districts of the state. Having estimated the responsiveness of decisions, particular attention is given to the indicated impact of government programs on observed farm decision-making behavior. The apparent importance of subjective risk in farm decisions and the effects of stabilization obtained through government programs are then made evident.

2 A DYNAMIC ECONOMETRIC MODEL OF PRODUCTION DECISIONS

In this study the general form of the econometric model for field crops will be assumed to be block recursive. Wold (1953 and 1964) and others have commonly regarded agricultural crop systems as recursive rather than simultaneous, thus allowing each of the blocks to be statistically investigated independently without loss of efficiency. For field crops, acreage allocation decisions are made on the basis of available information at the time of planting. After crops are planted, weather and other difficult-to-quantify factors, such as pests and crop diseases along with fertilizer and irrigation, determine yields. Subsequently, prices and other demand-related variables are determined. A distinct time lag takes place between the determination of each of these groups of variables preventing simultaneity.[2] Accordingly, the econometric investigation of field crop acreage response, yield, and demand can be dealt with independently. Hence, the acreage decision model in this study will be considered statistically, although not economically, independent of demand and yield determination.[3]

The Scope of the Model[4]

The first major objective of this study deals with development of a dynamic econometric model for production decisions made in an economic environment of changing risk. The method of model construction is essentially based on positive economic

[2] Although acreage harvested is often slightly less than acreage planted and should be considered simultaneously with yields, data are not sufficiently complete to maintain this distinction.

[3] Due to the lack of supply characteristics demonstrated by yield variation, the model for yield is not treated explicitly as part of the supply-response model. Yield appears to be influenced almost entirely by variables exogenous to the system such as weather, pests, the development of new varieties, the development of irrigation facilities, and currently approved fertilization practices. See Appendix A.

[4] Although the model is developed here for the specific purpose of estimating acreage response, the results will hold for any economic problem where decision-makers are faced with similar risk situations, e.g., portfolio analysis.

and decision theory. Although the classical theory of the firm has only limited applicability in dynamic problems such as this, the theory of economic risk bearing has now matured to the point that applications in econometric model building are possible with few additional assumptions. In classical microeconomic theory, decision-makers are generally assumed to possess full knowledge of the parameters of the economic systems in which they play an active role. Few decision-makers ever have such knowledge, and still they make decisions that carry economic significance. Accordingly, increasing theoretical work has been done in recent years on the stochastic nature of problems concerning the real world. Although the most common suggestion has been that an action should be evaluated according to the expected utility of the mean and variance of the corresponding probability distribution of outcomes (Markowitz, 1959; Tobin, 1958; 1969), not all authors have even found it necessary or desirable to accept the expected utility principle. Accordingly, the class of objective functions considered here will be kept on a general basis, although the family of subjective probability distributions held by decision-makers will be assumed quite specifically. Assuming that decision-makers view the economy as a Markovian environment in which the true state of the environment cannot be observed without error, the appropriate temporal relationship between information and decision variables is investigated. Implications are then drawn as to the kinds of distributed lag models that might be used for the econometric analysis of observed quantitative decisions.

Important Concepts

In the rigorous axiomatic theory of risk bearing, several quite plausible assumptions designed to characterize reasonable behavior under conditions of uncertainty give rise to a number of existence theorems associated with the decision-maker's problem of choice.[5] Although a rigorous treatment will not be of concern here, some of the concepts will be of particular interest. First of all, perhaps the most basic proposition (often stated as a postulate) in the theory of risk bearing is the existence of a preordering over prospects for each decision-maker.[6] The prospect associated with any action, or decision, d is usually defined for the case when the set of possible outcomes is finite as

$$p(d) \equiv (p_1, \ldots, p_k | d \in D)$$

where D is the set of all possible decisions and p_i is the probability that the action d results in the outcome r_i, $i = 1, \ldots, k$.[7] However, the assumption here will be that each possible outcome can be represented by a point in an m-dimensional space so that the case of an infinite set of possible outcomes can be handled easily. Correspondingly, a prospect is defined as

$$p(d) \equiv \{f_r(r | d \in D)\}$$

[5] Although the history of this development dates back to Bernoulli (1738), the major contributions referred to are those of Ramsey (1931), de Finetti (1937), von Neumann and Morgenstern (1953), and Savage (1954). Recent treatments can be found in Arrow (1971) and Marschak and Radner (1972).

[6] A binary relationship $\gtrsim$ is defined to be a preordering if it has the properties of comparability (for any two prospects p_1 and p_2, either $p_1 \gtrsim p_2$ or $p_2 \gtrsim p_1$ or both), transitivity (for any three prospects p_1, p_2, and p_3, if $p_1 \gtrsim p_2$ and $p_2 \gtrsim p_3$, then $p_1 \gtrsim p_3$) and reflexivity (for any prospect p_1, $p_1 \gtrsim p_1$).

[7] Much of the terminology employed here will be essentially that used by Marschak and Radner (1972) and Savage (1954).

where $f_r(\cdot)$ is the probability density function of the m-dimensional random vector r.[8] Whereas, the standard requirements are

$$p_i > 0 \quad \text{for } i = 1, \ldots, k$$

and

$$\sum_{i=1}^{k} p_i = 1,$$

we now require

$$f_r(r) \geq 0$$

and

$$\int f_r(r)\, dr = 1.$$

Although the original definition of consistency (of tastes, i.e., preference ordering on actions) employed, for example, by Debreu (1959) can be used even when risk is introduced, the concept of consistent beliefs described by Marschak and Radner (1972) will be of primary importance here. A decision-maker is said to have consistent beliefs if he can rank future alternative events according to his personal views of their comparative probabilities. While Marschak and Radner tie their development to the existence of a utility function that can be essentially used in maximizing expected utility, the only assumption really needed here is the existence of an ordering according to personal prospects.

A second concept of basic importance, which is often derived as a result of the axiomatic analysis of risk bearing (Arrow, 1971, chapter 2, section 4), is the existence of personal probability for future events. Although personal probability has also often been dealt with on a general level, for the purposes of this study the particular distribution of personal or subjective probability will be assumed quite specifically so that the number of parameters in the resulting econometric model will be manageable for estimation purposes. The basic dynamics of the resulting econometric model will then be due to the way in which personal probability is modified as new information on a perhaps changing economic environment is obtained. While the idea of personal probability and the modification of that probability (according to Bayes' theorem as more information becomes available) has been a subject of controversy, no other possibility seems to exist in the literature for the problem of adaptive control in a dynamic real world. Furthermore, the primary objection is to the use of the Bayesian principle as a means of scientific research. The possibility of different researchers obtaining different conclusions from the same data is argued to be scientifically undesirable. The use of the Bayesian approach in this study, however, is as a means of explaining decision-makers' behavior in a changing economic environment.

In this context then, consider an entrepreneur faced with the p-dimensional decision of determining the level of each of m resources to employ in each of q possible production processes ($p = m \times q$) in each production period. Suppose the decision in period t is denoted by d_t and is based on the entrepreneur's personal views of the comparative probabilities of any number of outcomes of interest (e.g., profits, sales, costs, productivities, etc.) associated with each possible decision. Let the vector of outcomes of interest in period t be denoted by r_t, with r_t determined by d_t and s_t where s_t is the observed state of the environment in period t.[9] That is,

[8] The existence of the probability density function is assumed since the specific family of the distribution must eventually be specified to obtain the econometric model.

[9] One might think of s_t as an n-dimensional vector composed of such things as prices of inputs, prices of outputs, productivities, etc.

$$r_t = r(d_t, s_t).$$

The decision-maker's observation s_t in each period can then be thought of as a noisy information signal. Based on the information signal received in period t, the decision-maker will modify his personal prospects by means of Bayes' theorem and choose the action corresponding to the highest ranking prospect for the next period. The decision correspondence is thus denoted by

$$d_{t+1} = d_{t+1}(s_t)$$

where the subscript of the correspondence denotes the dependence on the personal prospects held prior to reception of information in period $t + 1$.[10] In the usual decision theoretic framework, if the parameter vector of the environmental state process λ_t is distributed *a priori* by a decision-maker in period t as

$$\lambda_t \sim g_\lambda(\lambda_t)$$

where the distribution of the state s_t at t is

$$s_t \sim f_s(s_t|\lambda_t),$$

then the modification of personal probability when the state is actually observed is theoretically given by Bayes' theorem as[11]

$$g_\lambda(\lambda_t|s_t) \propto f_s(s_t|\lambda_t)\, g_\lambda(\lambda_t)$$

where $g_\lambda(\lambda_t|s_t)$ is the posterior personal probability density function.

To see how the new information will be used in making decisions for the next period, some specific assumptions must be made about the economic environment, but first the decision-makers' perception of the economic environment should be considered more closely. It might be argued that entrepreneurs believe certain primary forces, such as technology and tastes and preferences, underly the deterministic variation in the economic environment. Due to some unknown and/or stochastic forces, however, the observed state of the environment or the information received on the state of the environment might vary randomly around the true state of the environment which is actually indicative of the primary forces in the economy. For example, productivities can vary stochastically around some unknown productivity which is actually indicative of the true state of technology. This relationship corresponds to the stochastic variation of s_t around λ_t. Obviously, however, the determining forces of the true state of the environment are not fixed. Hence, the usual assumptions of sequential analysis or sequential decision theory must be generalized by allowing λ_t to vary with time. Before the construction of an econometric model can proceed, we must then specify how λ_t varies or, at least, how the

[10] For the purposes of this study, the entrepreneur is assumed to have only one source of information, his own observation of the economic environment, from which he receives exactly one signal every period. Furthermore, every decision-maker is assumed to observe the entire state vector even when some of the information pertains to production processes not used by the individual producer. This assumption was made necessary because stratified data were not available and could otherwise have been dropped. Although more interesting econometric models with several possible channels of information could be developed with this approach, data limitations often prevent such an analysis. For example, forecasting and consulting services should allow the decision-maker to improve his personal probability if the economic value of those channels to him exceeds their cost.

[11] It is convenient to make use of the proportionality symbol here so that all constant factors can be dropped. Also, note that throughout this paper, f will be used to denote objective distributions (distributions for which the parameters are not known) and g will be used to denote subjective distributions (distributions on the unknown parameters, the parameters of which are determined by the observer or decision-maker). The subscript of f or g, as the case may be, references the variable to which the distribution applies.

decision-maker views the variation of λ_t. Since such primary forces as technology and tastes and preferences are often considered to change in an unpredictable or random way and since the magnitudes of those forces in any given time period seem to be closely related to the most previous time periods, a reasonable assumption might be that λ_t is itself a Markov process, i.e.,[12]

$$\lambda_{t+1} \sim f_\lambda(\lambda_{t+1}|\lambda_t).$$

This would then be somewhat more general than the usual formulation where the observed environmental variables themselves are defined as Markov processes.[13] For example, Marschak and Radner (1972) discuss only first-order autoregressive and discrete-time Brownian motion (independent increments) cases of observed environmental information. Murphy (1965) treats only the case where the observed state is a Markov chain. In both treatments the true state is assumed to be observed. Howard (1960) and Blackwell (1962, 1965) have shown that, under such assumptions, Markov policies provide optimal stationary policies. Thus, information from period t becomes worthless to the decision-maker as soon as information at any period $t + k(k > 0)$ is obtained. Realistically, however, decisions are often based on information over several periods due to the relative level of noise in any one signal. Accordingly, only the parameter vector λ_t of the environmental process will be assumed to be a Markovian process in this study.[14] The posterior personal probability density function, $g_\lambda(\lambda_t|s_t)$, will then be used in forming prior beliefs for the next period according to Bayes' theorem as follows:[15]

$$g_\lambda(\lambda_{t+1}|s_t) \propto \int f_\lambda(\lambda_{t+1}|\lambda_t)\, g_\lambda(\lambda_t|s_t)\, d\lambda_t \propto \int f_\lambda(\lambda_{t+1}|\lambda_t) f_s(s_t|\lambda_t)\, g_\lambda(\lambda_t)\, d\lambda_t. \tag{1.1}$$

$$g_s(s_{t+1}|s_t) = \int f_s(s_{t+1}|\lambda_{t+1})\, g_\lambda(\lambda_{t+1}|s_t)\, d\lambda_{t+1}. \tag{1.2}$$

$$g_r(r_{t+1}|s_t, d_{t+1}) = g_s[r^{-1}(r_{t+1}, d_{t+1})|s_t]\,|J_{s,r}(r_{t+1}, d_{t+1})| \tag{1.3}$$

assuming the outcome function $r(\cdot,\cdot)$ is well behaved so that both the inverse function

$$s = r^{-1}(r, d),$$

and the Jacobian of the transformation from s to r,

$$J_{s,r}(r_{t+1}, d_{t+1}) = \frac{\partial r^{-1}(r_{t+1}, d_{t+1})}{\partial r_{t+1}},$$

[12] Of course, other more complicated assumptions could be justified on the basis of the simple motivation given. For example, λ_t could be assumed to be a more general autoregressive or moving-average process.

[13] Decision problems with Markovian state processes are termed Markovian decision processes. A wide selection of such problems can be found in Bellman (1957 and 1961), Howard (1960), and Martin (1967). Control processes for noisy state information, which essentially characterizes the assumptions used here, are discussed to a limited extent in Aoki (1967) and DeGroot (1970).

[14] The usual assumption of a directly observable Markov process will then be a special case where the distribution of s_t, given λ_t, is singular.

[15] The practice of using a posterior from one period as a prior for the next period is essentially that of sequential analysis introduced by Wald (1947). In this study, however, the posterior must further be modified on the basis of the knowledge of the underlying Markov process to form a prior for the next period since the distribution from which observations are obtained is changing.

exist. The personal prospects for $t + 1$ are then given by

$$p_{t+1}(d_{t+1}) = \{g_r(r_{t+1}|s_t, d_{t+1})\}, \tag{1.4}$$

so the decision correspondence becomes

$$d_{t+1} = d_{t+1}(s_t) = \{d_{t+1} \in D | p_{t+1}(d_{t+1}) \gtrsim p_{t+1}(d'_{t+1}) \quad \text{for all } d'_{t+1} \in D\}. \tag{1.5}$$

To obtain an econometric model for this decision process, the method will be that of determining the parameters of the subjective prospects and how they vary as information is acquired. Decisions can then be estimated on the basis of the variation in those parameters when stationary policies are employed. If the outcome function is known and the entrepreneur can rank possible decisions on the basis of their associated prospects, as in (1.5), then all the variation in decisions will be due to the variation in the parameters of the subjective distribution of s_t,

$$g_s(s_{t+1}|s_t),$$

which, in a continuing decision process, might be denoted as

$$g_s(s_{t+1}|s_t, s_{t-1}, \ldots).$$

A Model for Stationary Risk

Although an econometric model could be derived under general conditions if the state space were finite, the resulting model would have too many parameters to be statistically amenable to estimation unless only a very few states were possible (given usual data limitations). Indeed, much of the formal theory of risk bearing and the study of adaptive control processes considers only a finite state space where the conditions are satisfied for the state at $t + 1$, given the state at t to have a multinominal distribution. The environmental process is then a Markov chain. Given that the process is ergodic, all the personal transition probabilities would possibly be modified through time with the availability of new information. These modification procedures could then be used to derive an econometric model of decision-making behavior.

Consider, however, the more specific assumption that the observed state in period t is distributed multivariate normally

$$(s_t|\lambda_t) \sim N(\lambda_t, \Sigma^{-1}) \tag{1.6}$$

or

$$f_s(s_t|\lambda_t) \propto \exp\left[-\frac{1}{2}(s_t - \lambda_t)'\Sigma(s_t - \lambda_t)\right],$$

with $n \times 1$ mean vector λ_t and $n \times n$ positive definite precision matrix Σ,[16] and that the parameter vector λ_t (indicative of the true state of the economic environment) is itself a Markov process given by

$$(\lambda_t|\lambda_{t-1}) \sim N(\lambda_{t-1}, \omega\Sigma^{-1}) \tag{1.7}$$

or

$$f_\lambda(\lambda_t|\lambda_{t-1}) \propto \exp\left[-\frac{1}{2\omega}(\lambda_t - \lambda_{t-1})'\Sigma(\lambda_t - \lambda_{t-1})\right]$$

[16]Note that a precision matrix is defined as the inverse of the associated covariance matrix.

for some constant scalar $\omega > 0$. Suppose, further, that the entrepreneur's subjective knowledge at period t is described by a member of the standard conjugate family for a normal distribution with unknown mean, i.e., another normal distribution say,[17]

$$(\lambda_t | s_{t-1}, s_{t-2}, \ldots) \sim N\left(m_t, \frac{1}{\gamma_t}\Sigma^{-1}\right) \tag{1.8}$$

or

$$g_\lambda(\lambda_t | s_{t-1}, s_{t-2}, \ldots) \propto |\gamma_t \Sigma|^{1/2} \times \exp\left[-\frac{\gamma_t}{2}(\lambda_t - m_t)'\Sigma(\lambda_t - m_t)\right].$$

for some scalar $\gamma_t > 0$. On the basis of (1.6) and (1.8), we might then represent the subjective distribution of the observed state in period t prior to actual observation as[18]

$$(s_t | s_{t-1}, s_{t-2}, \ldots) \sim N\left(m_t, \frac{1}{\gamma_t}\Sigma^{-1} + \Sigma^{-1}\right) \tag{1.9}$$

where the subjective distribution of λ_t is independent of the distribution of s_t given λ_t. The entrepreneur's decision for period t would thus be based on (1.9) as indicated in (1.1) through (1.5).

Consider the possible revision of subjective knowledge upon observation of the economic state in period t. According to Bayes' theorem, the revision of subjective knowledge theoretically results in[19]

$$(\lambda_t | s_t, s_{t-1}, \ldots) \sim N\left[(1 - \theta_t)m_t + \theta_t s_t, \frac{1}{\gamma_t + 1}\Sigma^{-1}\right] \tag{1.10}$$

where

$$\theta_t = \frac{1}{\gamma_t + 1}.$$

On the basis of (1.7), the implied subjective distribution of the true state in period $t + 1$ is then

$$(\lambda_{t+1} | s_t, s_{t-1}, \ldots) \sim N\left[(1 - \theta_t)m_t + \theta_t s_t, \frac{1}{\gamma_t + 1}\Sigma^{-1} + \omega\Sigma^{-1}\right], \tag{1.11}$$

[17]The concept that will ultimately lead to the consideration of only subjective state parameters in the resulting econometric model will be the existence of optimal decision rules based solely on sufficient statistics of the information received. If a statistic is sufficient, any modification in subjective probabilities can be described completely by the prior probability distribution and the sufficient statistics of the sample. If the dimension of the sufficient statistic remains fixed regardless of the size of the sample, then there must exist a standard family of distributions such that if the subjective prior distribution of λ is in the family, then so also is the subjective posterior distribution of λ. Raiffa and Schlaifer (1961) have termed such families conjugate families. The use of a conjugate family member is then important since decision rules need only be based on sufficient statistics. For a more detailed discussion of these concepts, see DeGroot (1970).

[18]This is apparent since s_t might be alternatively represented as

$$s_t = \lambda_t + \delta_t$$

where

$$\delta_t \sim N(0, \Sigma^{-1}).$$

Using the subjective distribution for s_t given in (1.8) and the usual probability calculus for independent normal distributions (the mean of s_t is the sum of the means for λ_t and δ_t and the variance of s_t is the sum of the variances for λ_t and δ_t), the result in (1.9) is obtained.

[19]For a derivation of (1.10), see DeGroot (1970, Theorem 1, Section 9.9).

assuming the subjective distribution of λ_t is independent of the distribution of λ_{t+1} given λ_t.[20] Similarly, (1.6) indicates the corresponding subjective distribution for s_{t+1} would be

$$(s_{t+1}|s_t, s_{t-1}, \ldots) \sim N\left[(1-\theta_t)m_t + \theta_t s_t, \frac{1}{\gamma_t+1}\Sigma^{-1} + \omega\Sigma^{-1} + \Sigma^{-1}\right]. \quad (1.12)$$

Relationships (1.8) and (1.11) or (1.9) and (1.12) thus indicate the difference equations for m_t and γ_t,

$$m_{t+1} = (1-\theta_t)m_t + \theta_t s_t, \quad (1.13)$$

and

$$\frac{1}{\gamma_{t+1}}\Sigma^{-1} = \frac{1}{\gamma_t+1}\Sigma^{-1} + \omega\Sigma^{-1}$$

or

$$\gamma_{t+1} = \left[\frac{1}{\gamma_t+1} + \omega\right]^{-1}, \quad (1.14)$$

the solution of which is

$$\lim_{t\to\infty}\gamma_t = \frac{1}{2}(\sqrt{1+4/\omega} - 1) \equiv \gamma > 0$$

where γ is the equilibrium value of the difference relationship. We have thus shown that in time γ_t will approach the constant γ and, hence, θ_t will approach θ where

$$\theta = \frac{1}{\gamma+1}.$$

Whence, the solution of (1.13) is[21]

$$m_t = \theta\sum_{k=0}^{\infty}(1-\theta)^k s_{t-k-1}.$$

Since, as indicated under the assumptions above, all of the explainable variation in the decision vector is due to changes in the subjective distribution

$$g_s(s_t|s_{t-1}, s_{t-2}, \ldots)$$

and since m_t becomes the only changing parameter in the subjective distribution of s_t and in the decision correspondence in (1.5), entrepreneurial decisions should find adequate explanation in an econometric model of the form

$$d_t = d(m_t) = d\left[\theta\sum_{k=0}^{\infty}(1-\theta)^k s_{t-k-1}\right]$$

or

$$d_t = d(m_{t,1}, \ldots, m_{t,n}) \quad (1.15)$$

---

[20] This result is also apparent through the usual probability calculus for normal distributions since λ_{t+1} can be represented as

$$\lambda_{t+1} = \lambda_t + v_t$$

where

$$v_t \sim N(0, \omega\Sigma^{-1}).$$

Since v_t and λ_t are independent, we can add means and variances from (1.7) and (1.10) obtaining (1.11). Representing s_{t+1} as

$$s_{t+1} = \lambda_{t+1} + \delta_{t+1}$$

where $\delta_{t+1} \sim N(0, \Sigma^{-1})$ then also suggests the result in (1.12).

[21] Since γ is positive and $\theta = 1/(\gamma+1)$, θ will lie in the open interval (0, 1). Hence,

$$m_{t+1} = \lim_{t_0\to-\infty}\left[(1-\theta)^{t-t_0+1}m_{t_0} + \theta\sum_{k=0}^{t-t_0}(1-\theta)^k s_{t-k}\right] = \theta\sum_{k=0}^{\infty}(1-\theta)^k s_{t-k}$$

since $(1-\theta)^{t-t_0+1} = [\gamma/(\gamma+1)]^{t-t_0+1}$ and $\lim_{t_0\to-\infty}[\gamma/(\gamma+1)]^{t-t_0+1} = 0.$

where $m_{t,j} = \theta \sum_{k=0}^{\infty} (1 - \theta)^k s_{t-k-1,j}$ and $s_{t-k-1,j}$ is the jth element of s_{t-k-1}. In a linearized case the resultant model simply becomes a multivariate version of Cagan's adaptive expectations model (Griliches, 1967),

$$d_t = A_0 + \theta A_1 \sum_{k=0}^{\infty} (1 - \theta)^k s_{t-k-1} + \varepsilon_t \tag{1.16}$$

where A_0 and A_1 are $p \times 1$ and $p \times n$ parametric matrices, respectively, and ε_t is a stochastic disturbance vector.

A Model for Slowly Changing Risk

In the case of changing risk (i.e., a varying precision of the observed state s_t around the true state λ_t) precise results are not so easily obtainable. It is possible, however, to determine the temporal relationship of variables in the short run when risk changes slowly; thus, the set of stationary lag models assigning the indicated temporal relationships can be determined.

Suppose we retain assumptions (1.6) and (1.7) of the constant risk case but now add a time subscript to the precision martix Σ to represent changing risk so that

$$(s_t | \lambda_t, \Sigma_t) \sim N(\lambda_t, \Sigma_t^{-1})$$

and

$$(\lambda_t | \lambda_{t-1}) \sim N(\lambda_{t-1}, \Phi). \tag{1.17}$$

Suppose, also, that the entrepreneur's subjective knowledge of λ_t and Σ_t before observing s_t is described by a Wishart-normal distribution with[22]

$$(\lambda_t | \Sigma_t, s_{t-1}, s_{t-2}, \ldots) \sim N\left(m_t, \frac{1}{\gamma_t}\Sigma_t^{-1}\right) \tag{1.18}$$

or

$$g_\lambda(\lambda_t | \Sigma_t, s_{t-1}, s_{t-2}, \ldots) \propto |\gamma_t \Sigma_t|^{1/2} \times \exp\left[-\frac{\gamma_t}{2}(\lambda_t - m_t)' \Sigma_t (\lambda_t - m_t)\right]$$

and

$$(\Sigma_t | s_{t-1}, s_{t-2}, \ldots) \sim W(\alpha_t, \underline{\beta}_t)$$

or

$$g_\Sigma(\Sigma_t | s_{t-1}, s_{t-2}, \ldots) \propto |\Sigma_t|^{(\alpha_t - n - 1)/2} \exp\left[-\frac{1}{2} tr(\underline{\beta}_t \Sigma_t)\right]$$

where $W(\alpha_t, \underline{\beta}_t)$ represents a Wishart distribution with α_t degrees of freedom and positive definite parametric matrix $\underline{\beta}_t$. In this case the revision of subjective knowledge upon observation of the state of the economy s_t results in [23]

$$(\lambda_t | \Sigma_t, s_t, s_{t-1}, \ldots) \sim N\left[(1 - \theta_t)m_t + \theta_t s_t, \frac{1}{\gamma_t + 1}\Sigma_t^{-1}\right] \tag{1.19}$$

and

$$(\Sigma_t | s_t, s_{t-1}, \ldots) \sim W[\alpha_t + 1, \underline{\beta}_t + (1 - \theta_t)(s_t - m_t)(s_t - m_t)'] \tag{1.20}$$

where, again,

$$\theta_t = \frac{1}{\gamma_t + 1} \tag{1.21}$$

[22] The joint distribution of an $n \times 1$ vector λ and an $n \times n$ matrix Σ is defined to be Wishart-normal when λ, given Σ, is distributed as a multivariate normal, and the marginal distribution of Σ is Wishart.

[23] For a derivation of (1.19), see DeGroot (1970, Theorem 1, Section 9.10).

From (1.17), (1.19), and (1.20), the subjective distribution of the true state λ_{t+1} is then given by

$$(\lambda_{t+1}|\Sigma_t, s_t, s_{t-1}, \ldots) \sim N\left[(1-\theta_t)m_t + \theta_t s_t, \frac{1}{\gamma_t+1}\Sigma_t^{-1} + \Phi\right];$$

or where the Markov process for Σ_t represented by $f_\Sigma(\Sigma_{t+1}|\Sigma_t)$ is much more nearly singular than the distribution of $(\lambda_{t+1}|\Sigma_t, s_t, s_{t-1}, \ldots)$, the subjective prior distribution of the true state at $t+1$ is approximately given by

$$(\lambda_{t+1}|\Sigma_{t+1}, s_t, s_{t-1}, \ldots) \sim N\left[(1-\theta_t)m_t + \theta_t s_t, \frac{1}{\gamma_{t+1}}\Sigma_{t+1}^{-1}\right] \tag{1.22}$$

for some positive definite matrix Σ_{t+1} and scalar γ_{t+1}. Similarly, if $f_\Sigma(\Sigma_{t+1}|\Sigma_t)$ is much more nearly singular than the distribution of $(\Sigma_t|s_t, s_{t-1}, \ldots)$, then the distribution of $(\Sigma_{t+1}|s_t, s_{t-1}, \ldots)$ will approximate a Wishart distribution so that the prior subjective distribution for the observed state s_{t+1} approximates a Wishart-normal distribution given by (1.22) and

$$(\Sigma_{t+1}|s_t, s_{t-1}, \ldots) \sim W(\alpha_{t+1}, \underline{\beta}_{t+1})$$

where α_{t+1} and $\underline{\beta}_{t+1}$ depend on

$$\alpha_t^* = \alpha_t + 1$$

and

$$\underline{\beta}_t^* = \underline{\beta}_t + (1-\theta_t)(s_t - m_t)(s_t - m_t)'$$

through $f_\Sigma(\Sigma_{t+1}|\Sigma_t)$.[24] Assuming that the Markov process for Σ_t is such that

$$E(\Sigma_{t+1}|\Sigma_t) = \Sigma_t,$$

as we did for λ_t, also implies that the distributions of $(\Sigma_t|s_t, s_{t-1}, \ldots)$ and $(\Sigma_{t+1}|s_t, s_{t-1}, \ldots)$ have equal means, i.e.,[25]

[24] The importance of the slowness of movements in risk now becomes obvious. If the distribution given by $f_\Sigma(\Sigma_{t+1}|\Sigma_t)$ is too disperse, then the prior subjective density formed for s_{t+1} from the Wishart-normal posterior density for s_t may not be adequately represented by Wishart-normal parameters. Of course, certain other characteristics of $f_\Sigma(\Sigma_{t+1}|\Sigma_t)$ can help lead to a good approximation. For example, in certain univariate cases (where the Wishart distribution becomes a gamma distribution), the new prior distribution for s_{t+1} is exactly a Wishart-normal (gamma-normal) when $f_\Sigma(\Sigma_{t+1}|\Sigma_t)$ has the density function of an F distribution. A more detailed derivation of the approximate results stated here can be found in Just (1972).

[25] That is, since

$$\int \Sigma_{t+1} f_\Sigma(\Sigma_{t+1}|\Sigma_t)\, d\Sigma_{t+1} = \Sigma_t$$

where

$$g_\Sigma(\Sigma_t|s_t, s_{t-1}, \ldots) \propto |\Sigma_t|^{(\alpha_t - n)/2} \exp\left[-\frac{1}{2} tr(\beta_t^* \Sigma_t)\right]$$

and, thus, where

$$g_\Sigma(\Sigma_{t+1}|s_t, s_{t-1}, \ldots) \propto \int |\Sigma_t|^{(\alpha_t - n)/2} \exp\left[-\frac{1}{2} tr(\underline{\beta}_t^* \Sigma_t)\right] f_\Sigma(\Sigma_{t+1}|\Sigma_t)\, d\Sigma_t,$$

we obtain

$$E(\Sigma_{t+1}|s_t, s_{t-1}, \ldots) \propto \int \Sigma_{t+1}\, g_\Sigma(\Sigma_{t+1}|s_t, s_{t-1}, \ldots)\, d\Sigma_{t+1}$$
$$\propto \int |\Sigma_t|^{(\alpha_t - n)/2} \exp\left[-\frac{1}{2} tr(\underline{\beta}_t^* \Sigma_t)\right] \int \Sigma_{t+1} f(\Sigma_{t+1}|\Sigma_t)\, d\Sigma_{t+1}\, d\Sigma_t \propto \int \Sigma_t\, g_\Sigma(\Sigma_t|s_t, s_{t-1}, \ldots)\, d\Sigma_t.$$

Since $g_\Sigma(\Sigma_t|s_t, s_{t-1}, \ldots)$ is a Wishart distribution with parameters α_t^* and $\underline{\beta}_t^*$ and the mean of any Wishart distribution with parameters α and $\underline{\beta}$ is given by $\alpha\underline{\beta}^{-1}$, we find

$$E(\Sigma_{t+1}|s_t, s_{t-1}, \ldots) = E(\Sigma_t|s_t, s_{t-1}, \ldots)$$

or

$$\alpha_{t+1}\underline{\beta}_{t+1}^{-1} = \alpha_t^*(\underline{\beta}_t^*)^{-1}$$

verifying (1.23).

Thus, (1.23) implies

$$\alpha_{t+1} = \phi_t \alpha_t^*$$

and

$$\underline{\beta}_{t+1} = \phi_t \underline{\beta}_t^*$$

or

$$\alpha_{t+1} = \phi_t(\alpha_t + 1) \tag{1.24}$$

$$\underline{\beta}_{t+1} = \phi_t \underline{\beta}_t + \phi_t(1 - \theta_t)(s_t - m_t)(s_t - m_t)' \tag{1.25}$$

for some scalar ϕ_t possibly depending on α_t^* and $\underline{\beta}_t^*$. Also, (1.18) and (1.22) indicate the difference equation for m_t,

$$m_{t+1} = (1 - \theta_t)m_t + \theta_t s_t. \tag{1.26}$$

As indicated above, the variation in entrepreneurial decisions should depend solely on the variation of parameters of the subjective distribution of the economic state given in this case by (1.24), (1.25), and (1.26).[26] Hence, substituting the solutions of the difference equations given by (1.24), (1.25), and (1.26) into

$$d_t = d(m_t, \gamma_t, \alpha_t, \underline{\beta}_t) \tag{1.27}$$

where d_t is the p-dimensional decision at time t, we might examine the possible compatible stationary lag functions that could be used in the econometric analysis of decisions.

Since (1.21) implies θ_t and, hence, $(1 - \theta_t)$ are in the unit interval, we obtain from (1.26)

$$\begin{aligned} m_{t+1} &= \lim_{t_0 \to -\infty} \left\{ \left[\prod_{t^*=t_0}^{t} (1 - \theta_{t^*}) \right] m_{t_0} + \sum_{k=0}^{t-t_0} \left[\prod_{t^*=t-k+1}^{t} (1 - \theta_{t^*}) \right] \theta_{t-k} s_{t-k} \right\} \\ &= \sum_{k=0}^{\infty} \left[\prod_{t^*=t-k+1}^{t} (1 - \theta_{t^*}) \right] \theta_{t-k} s_{t-k}. \end{aligned} \tag{1.28}$$

It is thus clear that a stationary lag function, i.e., a function that includes s_{t-k} in the same way regardless of t, is only obtained when θ_t is constant, say, θ. Hence, from (1.21) and (1.28), a stationary lag function is only obtained when

$$m_{t+1} = \theta \sum_{k=0}^{\infty} (1 - \theta)^k s_{t-k} \tag{1.29}$$

and

$$\gamma_{t+1} = \frac{1}{\theta} - 1. \tag{1.30}$$

Moving to (1.25), we find

$$\begin{aligned} \underline{\beta}_{t+1} &= \lim_{t_0 \to -\infty} \left\{ \left[\prod_{t^*=t_0}^{t} \phi_{t^*} \right] \underline{\beta}_{t_0} + \sum_{k=0}^{t-t_0} \left[\prod_{t^*=t-k+1}^{t} \phi_{t^*} \right] (1 - \theta)(s_{t-k} - m_{t-k})(s_{t-k} - m_{t-k})' \right\} \\ &= \sum_{k=0}^{\infty} \left[\prod_{t^*=t-k+1}^{t} \phi_{t^*} \right] (1 - \theta)(s_{t-k} - m_{t-k})(s_{t-k} - m_{t-k})' \end{aligned}$$

assuming $0 < \phi_t < 1$.[27] If $\phi_t \geq 1$, then $\underline{\beta}_t$ would increase without bound so that any consideration of $\underline{\beta}_t$ in the econometric model would become degenerate in the

[26] Although a difference equation for γ_t has not been developed, sufficient implications for γ_t can be developed from the results relating to m_t and θ_t.

[27] Since α_t and $\underline{\beta}_t$ are always required to be positive and positive definite, respectively, under Wishart-normal assumptions, the relevant domain for ϕ can be restricted to be positive on the basis of (1.24) and (1.25). Hence, negative values of ϕ need not be considered.

long run. Again, it is clear that a stationary lag distribution is not obtained unless the weightings are independent of t, thus requiring ϕ_t to be a constant. Hence, $\underline{\beta}_{t+1}$ would become

$$\underline{\beta}_{t+1} = \sum_{k=0}^{\infty} \phi^k(1 - \theta)(s_{t-k} - m_{t-k})(s_{t-k} - m_{t-k})'. \tag{1.31}$$

Finally, the solution to (1.24) when ϕ_t is a constant, ϕ, and $0 < \phi < 1$ is found to be

$$\lim_{t \to \infty} \alpha_t = \frac{\phi}{1 - \phi}$$

so that α_t becomes constant when ϕ_t is constant. From (1.30), we also found that γ_t must become constant to obtain a stationary lag function. Hence, both α_t and γ_t can be excluded from the decision model in (1.27) since they have no possibilities for explaining the variation in decisions. The econometric model would thus become

$$d_t = d(m_t, \underline{\beta}_t)$$

where m_t and $\underline{\beta}_t$ are defined as in (1.29) and (1.31), respectively, or

$$d_t = d\{(m_{t,j}), (\underline{\beta}_{t,i,j})\} \tag{1.33}$$

where

$$m_{t,j} = \theta \sum_{k=0}^{\infty} (1 - \theta)^k s_{t-k-1,j},$$

$$\underline{\beta}_{t,i,j} = (1 - \theta) \sum_{k=0}^{\infty} \phi^k(s_{t-k-1,i} - m_{t-k-1,i})(s_{t-k-1,j} - m_{t-k-1,j}),$$

and $s_{t-k-1,i}$ is the ith element of s_{t-k-1}.

The resulting model is then similar to the adaptive expectations model in (1.15) or (1.16) except that geometric weightings of past observations on variability and covariability of the coordinates of the observed economic state are now included to capture the changes in decision-making behavior that might result with changes in risk. Since both variability and covariability are considered, however, the model should have the possibility of explaining diversification activities in addition to risk aversion tendencies.

Conclusions

Distributed lag models have generally been restricted to the class of stationary lag functions for the purposes of estimation since all but the most simple non-stationary lag models would require cross-section as well as time series data to obtain estimates of the variation in lag parameters through time, while the estimation procedures for any such models are bound to be exceedingly complex. Hence, we have also confined ourselves to the class of stationary lag functions in this study but, as indicated by the use of the word "function," we have considered more general models than are ordinarily used in distributed lag analysis. The resulting model in the changing risk case not only includes a simple distributed lag on past observations but also on cross-products of past observations.

Under quite simple and plausible environmental and distributional assumptions, we are then led to conclude that the possibility of changing risk precludes ordinary distributed lag analysis. The only stationary lag models of possible long-run appli-

cability in a noisy Markovian environment under the more general assumptions made herein would at least include (1.32) as a special case. In short-run situations of increasing subjective precision, no stationary lag distribution would be generally applicable.

An Alternative Explanation of the Decision Model

Interestingly, the resulting models in (1.15) and (1.32) are quite plausible on intuitive grounds and might be used empirically regardless of the above theoretical justification. The geometric lag distribution is often argued on intuitive grounds to provide a good approximation of the weightings attached by decision-makers to past observations in forming subjective expectations for the future. One can quickly verify that every subjective parameter included in the models in (1.15) and (1.32) can be interpreted as a subjective expectation for observed economic variables, an expected variance of observed variables about expectations, or an expected covariance between some pair of observed variables about their subjective expectations. Alternatively, one might simply postulate that, in the constant risk case (where variances and covariances are constant), decisions in a free market should depend only on decision-makers' subjective expectations and their set of possible decisions D determined by resource limitations and technological and institutional constraints. Assuming a constant D, the decision model would then simply obtain, as in (1.15),

$$d_t = d(m_t)$$

for some decision correspondence $d(\cdot)$ with

$$m_t = \theta \sum_{k=0}^{\infty} (1 - \theta)^k s_{t-k-1}$$

where

d_t = a p-dimensional decision (acreages of various crops, etc.)

m_t = an n-dimensional subjective expectation for the economic variables of interest (e.g., prices, yields, etc.)

θ = a geometric parameter in the unit interval

and

s_{t-k-1} = past observations of the economic variables of interest (information variables).

As indicated above, the linearized version of this constant risk model corresponds to Cagan's well-known adaptive expectations model and, of course, intuitive arguments have already been used many times to justify the empirical application of his simple geometric lag model.

In a situation of changing risk (i.e., where variances and covariances of observed information variables are changing), a similar way of including decision-makers' subjective variances and covariances of prices, yields, etc., might also be considered. If

$$(s_{t,i} - m_{t,i})^2 = \left[s_{t,i} - \theta \sum_{k=0}^{\infty} (1 - \theta)^k s_{t-k-1,i} \right]^2$$

(where i references the ith coordinates of the respective vectors) is regarded as an observation on the variance of $s_{t,i}$ about expectations, then decision-makers might form expectations for variances by geometrically weighting past observations of variance. Where ϕ is a scalar geometric parameter, the decision-maker's subjective expected variance of $s_{t,i}$ about his expectation for $s_{t,i}$ might be represented by

$$\underline{\tilde{\beta}}_{t,i,j} = (1 - \phi) \sum_{k=0}^{\infty} \phi^k (s_{t-k-1,i} - m_{t-k-1,i})^2.$$

Similarly, if $(s_{t,i} - m_{t,i})(s_{t,j} - m_{t,j})$ is regarded as an observation on the covariance of $s_{t,i}$ and $s_{t,j}$ about subjective expectations, the corresponding subjective expected covariance might be represented by

$$\underline{\tilde{\beta}}_{t,i,j} = \underline{\tilde{\beta}}_{t,j,i} = (1 - \phi) \sum_{k=0}^{\infty} \phi^k (s_{t-k-1,i} - m_{t-k-1,i})(s_{t-k-1,j} - m_{t-k-1,j}).$$

The decision correspondence for the case of changing risk would then also depend on subjective variances and covariances as in (1.33), i.e.,

$$d_t = d\{(m_{t,j}), (\underline{\tilde{\beta}}_{t,i,j})\}$$

or simply

$$d_t = d(m_t, \underline{\tilde{\beta}}_t)$$

where

$$\underline{\tilde{\beta}}_t = (\underline{\tilde{\beta}}_{t,i,j}) = (1 - \phi) \sum_{k=0}^{\infty} \phi^k (s_{t-k-1} - m_{t-k-1})(s_{t-k-1} - m_{t-k-1})'.$$

Since $\underline{\tilde{\beta}}_t$ differs from the $\underline{\beta}_t$ in (1.31) by only the constant scalar multiple $(1 - \phi)/(1 - \theta)$, the model obtained by this simple intuitive explanation is equivalent to the model in (1.32) which is used throughout the rest of this study.

3 A METHODOLOGY FOR INVESTIGATING THE IMPORTANCE OF GOVERNMENT INTERVENTION IN FARMER'S DECISIONS

Unfortunately, agricultural decision-makers do not operate in a simple uncontrolled environment such as described in section 2. Considerable complications have been added to the decision-making process as a result of the imposition and frequent revision of government farm commodity programs. It could be argued that a new econometric model is really needed to adequately investigate acreage response each time the provisions of government programs are changed. It would thus be impossible to locate enough time-series data to estimate the important indirect effects of a government program on uncontrolled crops or on crops controlled by other programs. The objective of this section, however, is to examine the possible effects of the various common forms of intervention on a free-market decision function. A methodology for combining time-series data from time periods governed by several combinations of programs can then be considered.[28] The government will be assumed to intervene in any combination of the following ways:

1. By the provision of subsidies or the imposition of taxes on outputs and inputs.
2. By the imposition of restrictions on the use of certain inputs.
3. By the establishment of price-support levels at which the government would purchase all of the commodity which could not clear the market at the resulting price.

[28] In a recent paper, Houck and Ryan (1972) have initiated research on a general methodology for evaluating farm commodity program effectiveness. However, their work fails to take any account of the important interdependent effects the government program forces might have.

For each case the production sector is assumed to be atomistic with each producer facing completely elastic supply and demand.

Subsidies and Taxes

Subsidies and taxes can enter the model described above in a quite simple fashion. In the case that subsidy and tax levels are announced prior to the commencement of the production process, special simplifications are possible (assuming producers are indifferent as to how much of the price paid [received] goes to [comes from] the government as opposed to other agents in the economy).

Consider partitioning the state variable s_t as

$$s_t = \begin{bmatrix} s_{1t} \\ s_{2t} \\ s_{3t} \end{bmatrix}$$

where s_{1t} is a vector of prices paid, s_{2t} is a vector of prices received, and s_{3t} is a vector of other information of importance to the firm (e.g., the productivity of various processes). Defining a location vector s_t^*,

$$s_t^* = \begin{bmatrix} s_{1t}^* \\ s_{2t}^* \\ 0 \end{bmatrix}$$

where s_{1t}^* is a vector of known taxes (per unit) on inputs and s_{2t}^* is a vector of known subsidies (per unit) for outputs ($s_{1t}^*, s_{2t}^* > 0$), the subjective distribution of s_t would then be simply modified on the basis of the location parameter s_t^*. Thus, the econometric model in (1.32) would become

$$d_t = d(m_t + s_t^*, \underline{\beta}_t)$$

where m_t is the subjective mean formulated on the basis of past prices exclusive of taxes and subsidies.

If taxes and subsidies are in some way stochastic, they might be treated in the same framework as the other variables for which subjective distributions are formed. If the underlying parameters of the tax and subsidy distributions are themselves Markov processes with other distributional assumptions similar to those used for s_t, then it would suffice simply to expand the dimension of the state vector s_t, the expectation vector m_t, and the associated parameter matrix $\underline{\beta}_t$. However, to avoid increasing the dimensionality of the econometric model, the tax and subsidy variables can be combined with the information vector s_t. With

$$(s_t | \lambda_t, \Sigma_t) \sim N(\lambda_t, \Sigma^{-1})$$

and

$$(s_t^{**} | \lambda_t^*, \Sigma_t^*) \sim N[\lambda_t^*, (\Sigma_t^*)^{-1}]$$

where s_t^{**} is a vector of stochastic taxes and subsidies with a structure corresponding to s_t, the tax and subsidy vector can be combined with s_t obtaining

$$(s_t + s_t^{**} | \lambda_t, \lambda_t^*, \Sigma_t, \Sigma_t^*) \sim N[\lambda_t + \lambda_t^*, \Sigma_t^{-1} + (\Sigma_t^*)^{-1}]$$

where λ_t^* and Σ_t^* are the mean vector and precision matrix, respectively, of the tax and subsidy distribution in period t. Substituting $s_t + s_t^{**}$ for s_t, $\lambda_t + \lambda_t^*$ for λ_t, and $\Sigma_t^{-1} + (\Sigma_t^*)^{-1}$ for Σ_t^{-1} in (1.17) through (1.31) would then obtain the model

$$d_t = d(m_t, \underline{\beta}_t)$$

where

$$m_t = \theta \sum_{k=0}^{\infty} (1 - \theta)^k (s_{t-k-1} + s^{**}_{t-k-1})$$

$$\underline{\beta}_t = \sum_{k=0}^{\infty} \phi^k (1 - \theta)(s_{t-k-1} + s^{**}_{t-k-1} - m_{t-k-1})(s_{t-k-1} + s^{**}_{t-k-1} - m_{t-k-1})'. \tag{2.2}$$

Restrictions on Input Use

Restrictions on input use are usually used in the control of agricultural production because of the stochastic nature of yields. Strict controls applied directly to production or sales would often result in the disposal of commodities after production. Connotations of social undesirability are often attached to such wastage, preventing public policies of direct production controls. Alternatively, an important input is chosen for restriction. The input that is chosen must be one that is not easily substitutable in production if the restriction is to have much effect. In the extreme case, let us assume that each firm has a fixed amount of some resource i at its disposal (e.g., tillable land in agricultural crop production) that is valuable enough in the production of some set of outputs so as to be always completely used in any production plan even when restrictions are imposed on the use of the input in the production of some subset of the outputs.

In such a case, the imposition of a restriction on input use would have the effect of limiting the set of possible decisions D in R^p, where d_t is again the real p-dimensional decision in D at time t. If p^* is the number of outputs for which resource i is possibly used as an input, then d_t might be partitioned as

$$d_t = \begin{bmatrix} d_t^* \\ \hline d_t^{**} \end{bmatrix}$$

where $d_t^* \in D^*$ is p^*-dimensional and specifies the amount of resource i used in the production of each of the p^* outputs.[29] Hence, when negative inputs of resource i are not possible, D^* can be simply described by the unit simplex in R^{p^*} where the amount of the resource available is normalized. That is,

$$\sum_{j=1}^{p^*} d_{tj}^* = 1 \tag{2.3}$$

where d_{tj}^* is the amount of the ith resource used in the production of the jth output. If the restriction

$$d_{tk}^* \leq \bar{d}_{tk}^*$$

is placed on the use of the resource in the production of the kth output and the restriction is effective, then D^* would simply be modified from (2.3) to

$$\begin{aligned} \sum_{\substack{j=1 \\ j \neq k}}^{p^*} d_{tj}^* &= 1 - \bar{d}_{tk}^* \\ d_{tk}^* &= \bar{d}_{tk}^* \end{aligned} \tag{2.4}$$

If the restriction is operative throughout the period for which the econometric model is intended, (2.4) would suggest that d_{tk}^* is simply explained by $\bar{d}_{tk}^*$ with the

[29] The implicit assumption made here is that production functions for different enterprises are essentially independent so the amount of resource i (land) used in the production of the jth output (crop) has meaning.

rest of the d_t^* vector being explained by $1 - \bar{d}_{tk}^*$ in addition to m_t and $\underline{\beta}_t$. If the restriction has not been continuously imposed, however, (2.4) would become

$$\left.\begin{aligned} \sum_{\substack{j=1\\ j\neq k}}^{p^*} d_{tj}^* &= 1 - \bar{d}_{tk}^* \\ d_{tk}^* &= \bar{d}_{tk}^* \end{aligned}\right\} \text{ for } t \in T_k^* \qquad (2.5)$$

$$\sum_{j=1}^{p^*} d_{tj}^* = 1 \qquad \text{for } t \in T_k^{**}$$

where T_k^* is the period in which the restriction on the use of resource i in the production of output k is imposed and T^{**} is the complement of T^* in T, the period of time for which the econometric model is intended. It would then be more convenient to modify (2.5) further so that a model with some degree of continuity can be obtained. Suppose $\tilde{d}_t^*$ is the set of decisions that would be made with respect to resource i in the absence of restrictions. Then, (2.5) could be written as

$$\left.\begin{aligned} \sum_{\substack{j=1\\ j\neq k}}^{p^*} d_{tj}^* &= 1 - \tilde{d}_{tk}^* + \Delta_{tk}^* \\ d_{tk}^* &= \tilde{d}_{tk}^* - \Delta_{tk}^* \end{aligned}\right\} \text{ for } t \in T$$

where Δ_{tk}^* is the decrease in the use of resource i in the production of output k resulting from the restriction, i.e.,

$$\Delta_{tk}^* = \begin{cases} \tilde{d}_{tk}^* - \bar{d}_{tk}^* & \text{for } t \in T_k^* \\ 0 & \text{for } t \in T_k^{**}. \end{cases}$$

Hence, the linearized model might be written as

$$d_t = A_0 + A_1 m_t + A_2 \beta_t + \tilde{A}_{3k}\Delta_{tk} + \varepsilon_t \qquad (2.6)$$

where A_0, A_1, A_2, and $\tilde{A}_{3k}$ are $p \times 1$, $p \times n$, $p \times (n/2)(n+1)$, and $p \times 1$ parameter vectors and matrices, respectively, and β_t is a vector version of $\underline{\beta}_t$, i.e.,[30]

$$\beta_t = \begin{bmatrix} \underline{\beta}_{t,1,1} \\ \vdots \\ \underline{\beta}_{t,1,n} \\ \underline{\beta}_{t,2,2} \\ \vdots \\ \underline{\beta}_{t,2,n} \\ \underline{\beta}_{t,3,3} \\ \vdots \\ \underline{\beta}_{t,n-2,n} \\ \underline{\beta}_{t,n-1,n-1} \\ \underline{\beta}_{t,n-1,n} \\ \underline{\beta}_{t,n,n} \end{bmatrix} \qquad (2.7)$$

[30] It may, of course, be interesting to allow A_1 and A_2 to change with the establishment of restrictions in any econometric investigation, but available time-series data in this study have prevented the inclusion of extra variables that such an analysis requires.

If the restriction is strictly met, the kth element of $\tilde{A}_{3k}$ might be appropriately constrained. Even with the restriction effective, however, the kth element of $\tilde{A}_{3k}$ might be slightly greater than what the restriction would indicate as a result of indivisibilities, etc.

In the above model, then,

$$\Delta^*_{tk} = A_{0k} + A_{1k\cdot} m_t + A_{2k\cdot} \beta_t - \bar{d}^*_{tk}$$

since $\tilde{d}^*_{tk}$ is the decision made with respect to the kth element of d_t in the absence of restrictions. In each case the k subscript references the kth element of each of the vectors except in the case of $A_{1k\cdot}$ and $A_{2k\cdot}$ which denote the kth row vectors of A_1 and A_2, respectively. Substituting in (2.6), the resulting model becomes nonlinear in parameters, thus requiring restrictions in any efficient estimation technique. Matters might be somewhat less complicated, however, if the other factors in the model are relatively constant. It would then suffice to estimate Δ^*_{tk} as

$$\Delta^*_{tk} = b_{1k} I_{tk} + b_{2k} \bar{d}^*_{tk} \tag{2.8}$$

where I_{tk} is a scalar indicator of the restriction period for the use of resource i in the production of output k,

$$I_{tk} = \begin{cases} 1, & \text{for } t \in T^*_k \\ 0, & \text{for } t \in T^{**}_k. \end{cases}$$

Other factors being nearly constant, $b_{1k} I_{tk}$ would estimate the nearly constant $\tilde{d}^*_{tk}$ and, hence, Δ^*_{tk} as in (2.8) would estimate $\tilde{d}^*_{tk} - \bar{d}^*_{tk}$. Thus, the model could be expressed as

$$\begin{aligned} d_t &= A_0 + A_1 m_t + A_2 \beta_t + b_{1k} I_{tk} \tilde{A}_{3k} + b_{2k} \bar{d}^*_{tk} \tilde{A}_{3k} + \varepsilon_t \\ &= A_0 + A_1 m_t + A_2 \beta_t + I_{tk} A_{3k} + \bar{d}^*_{tk} A_{4k} + \varepsilon_t \end{aligned} \tag{2.9}$$

where

$$A_3 = b_{1k} \tilde{A}_{3k} \tag{2.10}$$

and

$$A_4 = b_{2k} \tilde{A}_{3k}. \tag{2.11}$$

Although nonlinearities still persist in the model, fewer constraints need be imposed in any efficient estimation technique.

If the level of the restriction is also nearly constant during the period in which the restriction is imposed, matters can be further simplified. In such a case,

$$\bar{d}^*_{tk} \simeq b_{3k} I_{tk} \qquad \text{for all } t \in T^*_k$$

for some scalar constant b_{3k} so that

$$b_{1k} I_{tk} \tilde{A}_{3k} + b_{2k} \bar{d}^*_{tk} \tilde{A}_{3k} \simeq (b_{1k} + b_{2k} b_{3k}) I_{tk} \tilde{A}_{3k}. \tag{2.12}$$

If only the coefficient vector of I_{tk} is of interest and not the relative magnitudes of b_{1k}, b_{2k}, and b_{3k}, then the model in (2.9) can be adequately expressed as the linear model

$$d_t = A_0 + A_1 m_t + A_2 \beta_t + A^*_{3k} I_{tk} + \varepsilon_t \tag{2.13}$$

where

$$A^*_{3k} = (b_{1k} + b_{2k} b_{3k}) \tilde{A}_{3k}.$$

Hence, estimation is highly simplified.

Although quite restrictive assumptions have been used, the simplifications discussed here may, perhaps, often be applicable. Restrictions are usually placed on inputs to regulate an industry. For example, allotments imposed on agricultural crop pro-

duction usually have as a goal the stabilization of prices and production. Thus, if the goal is in some sense achieved, the other factors (represented in m_t and β_t) should be changing relatively little during the period of restriction. Furthermore, the restriction level would also not be varied greatly if stabilization is attained thus making (2.13) a model of practical applicability. Indeed, agricultural crop allotments have been revised relatively little compared to their magnitude in recent years.

Price Supports[31]

Price-support programs cannot be so simply included in the econometric model without increasing its dimensionality. In the simplest approach, price supports may be viewed as modifying decision-makers' subjective distributions of the economic state to be observed. Assuming (1) support prices are announced prior to the commencement of the production process and that (2) support programs are administered so as to prevent price from ever falling below the support level while being ineffective when a free market price above the support level occurs, the subjective distribution of the economic state in period t given by $g_s(s_t|s_{t-1}, s_{t-2}, \ldots)$ would become

$$g_s^*(s_t|s_{t-1}, s_{t-2}, \ldots) = \begin{cases} 0 & \text{for } s_{2t} \ngeq p_t \\ \displaystyle\int_{-\infty}^{p_t} g_s(s_t|s_{t-1}, s_{t-2}, \ldots)\, ds_{2t}^a & \text{for } s_{2t}^a = p_t^a,\ s_{5t}^b > p_t^b \\ g_s(s_t|s_{t-1}, s_{t-2}, \ldots) & \text{for } s_{2t} \gg p_t \end{cases}$$

where s_t is again partitioned with s_{2t} representing prices received, p_t is a vector of price-support levels in period t corresponding to s_{2t}, and the a and b superscripts represent any subpartition of the vectors s_{2t} and p_t. Thus, the set of changing explanatory variables in the econometric model would be augmented by p_t since the changes in $g_s(s_t|s_{t-1}, s_{t-2}, \ldots)$ would now be completely described by m_t, β_t, and p_t, i.e., $d_t = d(m_t, \beta_t, p_t)$. The linearization of the model might now, however, be somewhat more questionable. If the support level varied from several standard deviations below the expected price to some equal distance above the expected price, the relative effects of the support level as opposed to free market expectations would be very much different. However, the consequences of linearization should not be disastrous when effectiveness varies unless the probability of the effectiveness of a price support changes drastically. A support level may be effective in one period and not the next, while the probability of effectiveness remains constant. Changes in support levels can possibly be well correlated with expectations in some cases so that the probability of effectiveness varies relatively little. For example, the support levels offered for various agricultural commodities are often highly influenced by the administration's expectations of free market price and demand. Hence, if the administration's expectations are to some degree correlated with private expectations, the probability of price-support effectiveness might not vary greatly.

Voluntary Programs

Finally, the introduction of voluntary government programs complicates the government program component of the model. According to the analysis in the

[31] Although only price-support programs for outputs are specifically referred to here, the same mechanism would also carry through if minimum input price programs were of interest.

first part of this study that led to the model in (1.32), compliance with voluntary government programs might be treated as an indicator decision variable thus increasing the dimension of the decision vector. However, voluntary programs have not been in effect long enough to allow such an analysis by time series data when important interdependencies of programs are also considered. Hence, for the purposes of this study, the proportion of acreage in compliance with government programs is treated as exogenous.

Treating price supports in a linearized fashion, the jth equation of the model in (1.32) might be written to represent full compliance when only the kth program is offered as

$$d_{tj} = A_{0j} + A_{1j\cdot} m_t + A_{2j\cdot} \beta_t + A_{3jk} I_{tk} + A_{4jk} \bar{d}^*_{tk} + A_{5jk} p_{tk} + \varepsilon_{tj}$$

where m_t and β_t are defined by (2.2) and (2.7), the j subscript references the jth coordinates of the $p \times 1$ vectors d_t, A_0, A_{3k}, A_{4k}, and A_{5k}, while $A_{1j\cdot}$ and $A_{2j\cdot}$ represent the jth rows of A_1 and A_2. If there were no compliance, then (assuming price-support benefits are lost in the absence of compliance), the linear model would simply correspond to (1.32),

$$d_{tj} = A_{0j} + A_{1j\cdot} m_t + A_{2j\cdot} \beta_t + \varepsilon_{tj}.$$

Thus, a reasonable way to deal with a voluntary program for the kth decision variable where ψ_{tk} is the proportion of the restricted input used in compliance with government programs would be to use the model

$$d^c_{tj} = \psi_{tk}[A_{0j} + A_{1j\cdot} m_t + A_{2j\cdot} \beta_t + A_{3jk} I_{tk} + A_{4jk} \bar{d}^*_{tk} + A_{5jk} p_{tk} + \varepsilon_{tj}] \quad (2.14)$$

for complying response and the model

$$d^n_{tj} = (1 - \psi_{tk})[A_{0j} + A_{1j\cdot} m_t + A_{2j\cdot} \beta_t + A_{5jk}(1 - I_{tk}) p_{tk} + \varepsilon_{tj}] \quad (2.15)$$

for noncomplying response.[32] The total response for the jth decision variable would then be

$$\begin{aligned} d_{tj} = {} & A_{0j} + A_{1j\cdot} m_t + A_{2j\cdot} \beta_t + A_{3jk} \psi_{tk} I_{tk} \\ & + A_{4jk} \psi_{tk} \bar{d}^*_{tk} + A_{5jk}(\psi_{tk} + 1 - I_{tk}) p_{tk} + \varepsilon_{tj}. \end{aligned} \quad (2.16)$$

Following (2.14), (2.15), and (2.16), we might express the model for all decisions when q different possibly voluntary programs are offered as

$$d_t = A_0 + A_1 m_t + A_2 \beta_t + A_3 I^*_t + A_4 d^{**}_t + A_5 p^*_t + \varepsilon_t$$

where A_3, A_4, and A_5 are $p \times q$ matrices with elements A_{3jk}, A_{4jk}, and A_{5jk} in the jth rows and kth columns, respectively, and where the kth coordinates of I^*_t, d^{**}_t, and p^*_t are given by

$$I^*_{tk} = \psi_{tk} I_{tk},$$
$$d^{**}_{tk} = \psi_{tk} \bar{d}^*_{tk},$$

and

$$p^*_{tk} = (\psi_{tk} + 1 - I_{tk}) p_{tk},$$

respectively.[33]

Participation in voluntary diversion programs can also be treated exogenously in a similar manner. Indeed, a good part of diversion activities are influenced by

[32] The term $A_{5jk}(1 - I_{tk})p_{tk}$ enters (2.15) since farmers get full price-support provisions when allotments are not imposed.

[33] Although it would also be desirable to define ψ_{tkj}, which would be the proportion of compliance with the kth program by producers of the jth crop, such data are not available on a marco level.

government-controlled minimum and maximum diversion levels. As administered during the 1960's, the effect of the voluntary diversion programs was to reduce the effective restriction on the acreage of the crop in question. Other crops remained essentially unaffected except through the original allotment restriction since diverted acreage could not be used to produce other crops.[34] Hence, for any equation of the model

$$d_{tj} = A_{0j} + A_{1j}.m_t + A_{2j}.\beta_t + A_{3j}.I_t^* + A_{4j}.d_t^{**} + A_{5j}.p_t^* + \varepsilon_{tj}, \tag{2.17}$$

d_t^{**} can simply be changed to $\bar{d}_t^{**}$ where

$$\bar{d}_{tk}^{**} = \begin{cases} d_{tj}^{**} - d_{tj}^{+} & \text{for } k = j \\ d_{tk}^{**} & \text{for } k \neq j \end{cases} \tag{2.18}$$

and d_{tj}^{+} is the diversion associated with the jth decision variable. However, one might want to investigate the possibility that some of the diversion of cropland might have occurred regardless of government program activities. The diversion variable might then be considered independently thus possibly obtaining a coefficient considerably less than one in absolute value. If in (2.18)

$$\bar{d}_{tj}^{**} = d_{tj}^{**} - b_{4j}d_{tj}^{+}, \tag{2.19}$$

then (2.17) would become

$$d_{tj} = A_{0j} + A_{1j}.m_t + A_{2j}.\beta_t + A_{3j}.I_t^* + A_{4j}.d_t^{**} + A_{5j}.p_t^* + A_{6j}d_{tj}^{+} + \varepsilon_{tj}$$

where

$$A_{6j} = -b_{4j}A_{4jj}. \tag{2.20}$$

Another possibility which must be considered, since diversion levels are often constrained as a fixed percentage of the participating allotment or base, is that

$$d_{tj}^{+} \simeq b_{5j}d_{tj}^{**} \tag{2.21}$$

for some constant b_{5j}. If such is the case, then in the jth equation

$$A_{4j}.d_t^{**} + A_{6j}d_{tj}^{+} \simeq A_{4j}.d_t^{**} + A_{6j}\bar{b}_{5j}d_t^{**} = A_{4j}^*.d_t^{**}$$

where $\bar{b}_{5j}$ is a row vector with kth element

$$\bar{b}_{5jk} = \begin{cases} b_{5j} & \text{for } k = j \\ 0 & \text{for } k \neq j \end{cases}$$

and

$$A_{4j}^*. = A_{4j}. + A_{6j}\bar{b}_{5j}. \tag{2.22}$$

If the relationship in (2.12) also holds, then

$$d_{tk}^{**} \simeq b_{3k}I_{tk}^* \qquad \text{for all } k$$

or

$$d_t^{**} \simeq \bar{b}_3 I_t^* \tag{2.23}$$

where $\bar{b}_3$ is some constant $q \times q$ diagonal matrix with diagonal element b_{3k}. Hence,

$$A_{3j}.I_t^* + A_{4j}.d_t^{**} + A_{6j}d_{tj}^{+} \simeq A_{3j}.I_t^* + A_{4j}^*.d_t^{**} \simeq (A_{3j}. + A_{4j}^*.\bar{b}_3)I_t^* \simeq A_{3j}^{+}.I_t^*$$

where

$$A_{3j}^{+}. = A_{3j}. + A_{4j}^*.\bar{b}_3.$$

[34] There have been a few exceptions to this rule. For example, under the voluntary feed-grain programs, safflower acreage has qualified as diverted acreage although only half the usual diversion payment has been made for land diverted to safflower production.

Hence, four versions of the government program model can possibly be used depending on which combination of the assumptions in (2.21) and (2.23) are made. If both assumptions are employed, then an appropriate model would be

$$d_{tj} = A_{0j} + A_{1j}.m_t + A_{2j}.\beta_t + A^{+}_{3j}.I^{*}_t + A_{5j}.p^{*}_t + \varepsilon_{tj}. \tag{2.24}$$

If only (2.21) is imposed, the model would become[35]

$$d_{tj} = A_{0j} + A_{1j}.m_t + A_{2j}.\beta_t + A_{3j}.I^{*}_t + A^{*}_{4j}.d^{**}_t + A_{5j}.p^{*}_t + \varepsilon_{tj}. \tag{2.25}$$

When only (2.23) holds, one might consider

$$d_{tj} = A_{0j} + A_{1j}.m_t + A_{2j}.\beta_t + A^{*}_{3j}.I^{*}_t + A_{5j}.p^{*}_t + A_{6j}d^{+}_{tj} + \varepsilon_{tj}. \tag{2.26}$$

Finally, the most general version of the model is obtained when neither assumption is imposed,[36]

$$d_{tj} = A_{0j} + A_{1j}.m_t + A_{2j}.\beta_t + A_{3j}.I^{*}_t + A_{4j}.d^{**}_t + A_{5j}.p^{*}_t + A_{6j}d^{+}_{tj} + \varepsilon_{tj}. \tag{2.27}$$

Additional models could also be obtained if b_{4j} in (2.19) and (2.20) were constrained equal to one as in (2.18).

Problems of Aggregation

The econometric model presented thus far is a model for a single decision-maker. Unfortunately, however, data at the firm level are not readily available; and even if they were, the number of firms would be too great to permit computational feasibility. We are then forced to carry the implications of decision-making in a single firm to the industry level although, due to the nonlinearities in the model, unbiased aggregation is not generally possible. Suppose the most general model in (2.27) is rewritten as

$$d^i_t = A^i_0 + A^i_1 m^i_t + A^i_2 \beta^i_t + A^i_3 I^{*}_t + A^i_4 d^{**}_{ti} + A^i_5 p^{*}_{ti} + A^i_6 d^{+}_{ti} + \varepsilon^i_t \tag{2.28}$$

where the i superscript or subscript, as the case may be, is added to denote the ith decision-maker. Consider estimating the corresponding industry equation,

$$d_t = A_0 + A_1 m_t + A_2 \beta_t + A_3 I^{*}_t + A_4 d^{**}_t + A_5 p^{*}_t + A_6 d^{+}_t + \varepsilon_t, \tag{2.29}$$

where

$$d_t = \sum_i d^i_t.$$

Of course, I^{*}_t is an indicator variable when programs are not voluntary so that no bias results if we define

$$A_3 = \sum_i A^i_3.$$

[35] Recalling the assumptions in (2.10), (2.11), and (2.22), which have led to (2.25), it is evident that constraints need to be imposed from equation to equation if efficient estimators are to be obtained. From (2.10) and (2.11)

$$A_4 = A_3 \bar{b}_{12}$$

where $\bar{b}_{12}$ is a $q \times q$ diagonal matrix with diagonal element b_{2k}/b_{1k}. From (2.22)

$$A^{*}_4 = A_4 + A_6 \bar{b}_5$$

where A_6 and $\bar{b}_5$ are $q \times q$ diagonal matrices with diagonal elements A_{6j} and b_{5j}, respectively. Hence, A^{*}_4 should be proportional to A_3 except for the diagonal.

[36] Since (2.10) and (2.11) imply

$$A_4 = A_3 \bar{b}_{12}$$

where $\bar{b}_{12}$ is a $q \times q$ diagonal matrix with diagonal element b_{2k}/b_{1k}, constraints would also need to be imposed from equation to equation if efficient estimators of A_3 and A_4 in (2.27) were to be obtained.

Since allotments are contracted or expanded more or less proportionally for all farmers when the statewide allotment is contracted or expanded, we can reasonably write

$$d_{ti}^{**} = c_i d_t^{**}$$

where c_i is an $n \times n$ diagonal matrix of constants. Thus, defining

$$A_4 = \sum_i A_4^i c_i,$$

the conditions for exact aggregation would be satisfied since

$$A_4 d_t^{**} = \sum_i A_4^i c_i d_t^{**} = \sum_i A_4^i d_{ti}^{**}.$$

Also, since price-support levels generally differ only by a constant amount from one area of the state to another (essentially the transportation cost), we can write

$$p_{ti} = p_t + c_i^*$$

where c_i^* is a vector of the same dimension as p_t. Hence, defining

$$A_5 = \sum_i A_5^i$$

and

$$A_0 = \sum_i A_0^i - \sum_i A_5^i c_i^*,$$

the only resulting bias would be in the constant term; and that could possibly be zero depending on the distribution of c_i^* among decision-makers.[37]

More difficulty is encountered with the subjective variables m_t and β_t, however. In general, if θ, ϕ, or s_t varies over decision-makers, exact aggregation is not possible. A useful approximation can still be obtained, however, if

$$\begin{aligned}
E[m_{tj}^i/m_{tj}] &\simeq 1 && j = 1, \ldots, n \\
E[\beta_{tj}^i/\beta_{tj}] &\simeq 1 && j = 1, \ldots, \frac{n}{2}(n+1) \\
E[A_{1kj} m_{tj}^i/m_{tj}] &\simeq E[A_{1kj}^i] && j = 1, \ldots, n;\ k = 1, \ldots, p \\
E[A_{2kj} \beta_{tj}^i/\beta_{tj}] &\simeq E[A_{2kj}^i] && j = 1, \ldots, \frac{n}{2}(n+1);\ k = 1, \ldots, p
\end{aligned} \tag{2.30}$$

where j references the jth elements of the respective vectors and the expectations are taken over decision-makers at any given time t. Of course, exact aggregation would be obtained if

$$A_1 m_t = \sum_i A_1^i m_t^i$$

and

$$A_2 \beta_t = \sum_i A_2^i \beta_t^i$$

or more simply when

$$\begin{aligned}
A_{1kj} &= \sum_i A_{1kj}^i m_{tj}^i/m_{tj} && j = 1, \ldots, n;\ k = 1, \ldots, p \\
A_{2kj} &= \sum_i A_{2kj}^i \beta_{tj}^i/\beta_{tj} && j = 1, \ldots, \frac{n}{2}(n+1);\ k = 1, \ldots, p.
\end{aligned} \tag{2.31}$$

[37] These results and others, in the theory of linear aggregation, can be found in Theil (1954 and 1971). Unfortunately, however, we cannot apply linear aggregation theory in the rest of the model as θ, ϕ, and s_t all enter nonlinearly.

Under the assumptions in (2.30), conditions for exact aggregation in (2.31) then at least hold approximately in expectations. Furthermore, the conditions in (2.30) are quite plausible when one considers the atomistic aspects of the industry and the meaning of m_t and β_t. Theoretical implications of pure competition indicate the prices observed by various decision-makers should be equal for every period t. If all subjective knowledge is based on the same information, then one would expect the subjective parameters to be nearly the same for all decision-makers at any given time. Hence, adding the stochasticization associated with yields, we might plausibly consider the conditions in (2.30) to hold.

Consider, however, further assuming that

$$s_t = s_t + \tilde{c}_i \tag{2.32}$$

where $\tilde{c}_i$ is a constant vector associated with the ith decision-maker's managerial ability, spatial dislocation from the markets of interest, etc. Then, if θ and ϕ are equal for all decision-makers, we obtain

$$m_t^i = m_t + c_i$$

and

$$\beta_t^i = \beta_t.$$

Hence, defining

$$A_1 = \sum_i A_1^i,$$

$$A_2 = \sum_i A_2^i,$$

and

$$A_0 = \sum_i A_0^i = \sum_i A_1^i \tilde{c}_i,$$

the only aggregation bias resulting would be in the constant term.

On the basis of the structure of the field crop industry, however, it appears that, if θ and ϕ vary over decision-makers, the aggregation bias might be improved somewhat by allowing θ and ϕ to vary over crops. For example, each equation of the system in (2.29) might include a different subset of the total number of decision-makers. Thus, the average m_{tj}^i for farmers included in one equation might be different from the average m_{tj}^i over all farmers due to the difference in the average θ_i's. Similar consequences might be found in the case of β_t^i and ϕ_i. Hence, for purposes of estimation in this study, θ and ϕ will not be constrained equal over all equations.

4 POSSIBLE PROCEDURES FOR THE ESTIMATION OF PRODUCTION DECISIONS WITH GOVERNMENT INTERVENTION

Stochastic Aspects of the Model

Thus far, the source of disturbance terms in the model has been ignored. However, to develop appropriate estimation techniques, it is necessary to examine the various ways in which random variation might occur in the observed data. Recall the linearized version of the model in (1.32) augmented by the possibilities of government intervention as in (2.27):

$$d_t = A_0 + A_1 m_t + A_2 \beta_t + A_3 I_t^* + A_4 d_t^{**} + A_5 p_t^* + A_6 d_t^+ + \varepsilon_t. \tag{3.1}$$

The stochastic disturbance term, ε_t, might possibly result from any of the following phenomena:[38]

1. Stochastic measurment of decisions.
2. Randomization in the decision correspondence.
3. Approximation by continuous or linear decision functions.
4. Stochastic information reception.
5. Stochastic measurement of information.

In each of the five cases, the distrubance terms will be assumed to be independent of disturbances arising from other phenomena and to have zero expectations.

Stochastic measurement of decisions would simply imply the existence of errors in the observed d_t's. The assumption often made in econometric work is

$$E(\varepsilon_{1,t}\varepsilon'_{1,t-k}) = \begin{cases} \tilde{\Sigma}_1 & \text{for } k = 0, \\ 0 & \text{for } k > 0, \end{cases} \tag{3.2}$$

where $\tilde{\Sigma}_1$ is positive definite, $d_t = d_t^a + \varepsilon_{1,t}$, and d_t^a is the actual decision vector Thus, $\varepsilon_{1,t}$ is simply white noise and can be included as an additive disturbance with no difficulty in estimation. The possibility might also be considered, however, that the $\varepsilon_{1,t}$'s are serially correlated, i.e.,

$$\varepsilon_{1,t} = \rho_1 \varepsilon_{1,t-1} + e_{1,t}, \tag{3.3}$$

where

$$\rho_1 = \begin{bmatrix} \rho_{11} & 0 & \dots & 0 \\ 0 & \rho_{12} & \dots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \dots & \rho_{1p} \end{bmatrix},$$

$$E(e_{1,t}) = 0,$$

and

$$E(e_{1,t}e'_{1,t-k}) = \begin{cases} \tilde{\Sigma}_1 & \text{for } k = 0, \\ 0 & \text{for } k > 0. \end{cases}$$

For example, in a practical situation, statisticians often use bench-mark data (e.g., census data) to correct sample indications. Thus, the data available for use in econometric work may perhaps have some serial relationship as in (3.3).

Randomization in the decision correspondence would imply that decision-makers commit errors in selecting decisions according to (1.5). A reasonable assumption might be

$$E(\varepsilon_{2,t}\varepsilon'_{2,t-k}) = \begin{cases} \tilde{\Sigma}_2 & \text{for } k = 0, \\ 0 & \text{for } k > 0, \end{cases} \tag{3.4}$$

where ε_{2t} is the additive random part of the decision. However, if the randomization is due to some kind of random preference over prospects, then we might also want to allow the possibility that random disturbances tend to persist, i.e.,

$$\varepsilon_{2,t} = \rho_2 \varepsilon_{2,t-1} + e_{2,t}, \tag{3.5}$$

[38] Of course, we might also consider a random p_t vector, but that case is easily handled in the usual regression framework.

where

$$\rho_2 = \begin{bmatrix} \rho_{21} & 0 & \dots & 0 \\ 0 & \rho_{22} & \dots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \dots & \rho_{2p} \end{bmatrix},$$

$$E(e_{2,t}) = 0,$$

and

$$E(e_{2,t}e'_{2,t-k}) = \begin{cases} \tilde{\Sigma}_2 & \text{for } k = 0, \\ 0 & \text{for } k > 0. \end{cases}$$

The approximation of some decision correspondence by the linear model in (3.1) might also give rise to error terms due to the discontinuities and nonlinearities that might be inherent in a correspondence such as (1.5). Although the properties of the preference ordering and decision correspondence that make a continuous or linear version of the model fit well have not been discussed, it is clear that the decision correspondence need not be exactly linear or continuous to gain a good explanation with the model. For example, the decision correspondence could in reality vary in some manner around the linear function in (3.1). If the variance of d_t about the linear relationship is not uniform throughout D, then heteroskedastic assumptions might be needed for estimation. For the purposes of this study, though, the assumption will be

$$E(\varepsilon_{3,t}) = 0,$$

$$E(\varepsilon_{3,t}\varepsilon'_{3,t-k}) = \begin{cases} \tilde{\Sigma}_3 & \text{for } k = 0, \\ 0 & \text{for } k > 0, \end{cases} \tag{3.6}$$

where the difference in the correspondence (1.5) and the linear relationship in (3.1) is given by $\varepsilon_{3,t}$.

The last two sources of disturbances—stochastic information reception and stochastic measurement of information—lead to much more complicated assumptions for estimation purposes and would be perhaps more important sources of serial correlation. Stochastic information reception, not to be confused with stochastic information, implies that the observation, $\tilde{s}_t$, used by the decision-maker has some stochastic relationship with the s_t used as data in the estimation of the model. Stochastic information, on the other hand, was assumed as an underlying phenomenon giving rise to the model in (1.32) and refers to the stochastic nature of s_t itself. A reasonable assumption might be

$$\tilde{s}_t = s_t + e^*_{4,t}, \tag{3.7}$$

where

$$E(e^*_{4,t}) = 0$$

and

$$E[e^*_{4,t}(e^*_{4,t-k})'] = \begin{cases} \tilde{\Sigma}_4 & \text{for } k = 0, \\ 0 & \text{for } k > 0. \end{cases}$$

The subjective parameter, $\tilde{m}_t$ (associated with $\tilde{s}_t$ as m_t is with s_t), formed by the decision-maker would then be given by

$$m_t = \theta \sum_{k=0}^{\infty} (1-\theta)^k \tilde{s}_{t-k-1} = \theta \sum_{k=0}^{\infty} (1-\theta)^k s_{t-k-1} + \theta \sum_{k=0}^{\infty} (1-\theta)^k e^*_{4,t-k-1} = m_t + e_{4,t},$$

and the additive disturbance in the model would be

$$A_1 e_{4,t} = \theta \sum_{k=0}^{\infty} (1 - \theta)^k A_1 e^*_{4,t-k-1}.$$

Hence,

$$A_1 e_{4,t} = (1 - \theta) A_1 e_{4,t-1} + \theta A_1 e^*_{4,t-1},$$

which is essentially equivalent to (3.5) for estimation purposes. However, more disturbing results are obtained in the case of $\underline{\beta}_t$. Consider the subjective parameter, $\underline{\tilde{\beta}}_t$, formed by the decision-maker,

$$\underline{\tilde{\beta}}_t = \sum_{k=0}^{\infty} (1 - \theta)\phi^{k+1} \left[\tilde{s}_{t-k-1} - \theta \sum_{h=0}^{\infty} (1 - \theta)^h \tilde{s}_{t-k-h-2} \right]$$
$$\times \left[\tilde{s}_{t-k-1} - \theta \sum_{j=0}^{\infty} (1 - \theta)^j \tilde{s}_{t-k-j-2} \right]$$

Expanding and substituting (3.7),

$$\underline{\tilde{\beta}}_t = \underline{\beta}_t + \sum_{k=0}^{\infty} (1 - \theta)\phi^{k+1} \Bigg[s_{t-k-1}(e^*_{4,t-k-1})' + e^*_{4,t-k-1} s'_{t-k-1}$$
$$+ e^*_{4,t-k-1}(e^*_{4,t-k-1})' - \theta \sum_{h=0}^{\infty} (1 - \theta)^h s_{t-k-h-2}(e^*_{4,t-k-1})'$$
$$- \theta \sum_{j=0}^{\infty} (1 - \theta)^j e^*_{4,t-k-1} s'_{t-k-j-2}$$
$$+ \theta^2 \sum_{h=0}^{\infty} \sum_{j=0}^{\infty} (1 - \theta)^{j+h} (s_{t-k-h-2} e^{*\prime}_{4,t-k-j-2} + e^*_{4,t-k-h-2} s'_{t-k-j-2}$$
$$+ e^*_{4,t-k-h-2} e^{*\prime}_{4,t-k-j-2}) \Bigg]$$
$$= \underline{\beta}_t + \underline{e}_{4,t},$$

where $\underline{e}_{4,t}$ is a disturbance matrix defined by the above equation. Hence, the additive disturbance, $A_2 \tilde{e}_{4,t}$ (where $\tilde{e}_{4,t}$ is related to $\underline{e}_{4,t}$ as β_t is to $\underline{\beta}_t$), does not in general have a zero expectation since

$$E(\underline{e}_{4,t}) = \frac{2(1 - \theta)\phi}{(2 - \theta)(1 - \theta)} \tilde{\Sigma}_4.$$

Although unbiased estimation of all coefficients except A_0 and unbiased prediction are still usually possible even with biased estimation of A_0, matters continue to be complicated by the fact that $E(\tilde{e}_{4,t}\tilde{e}'_{4,t})$ depends on s_t. Defining

$$\tilde{A}_0 = A_0 + A_2 E(\tilde{e}_{4,t})$$
$$e_{5,t} = \tilde{e}_{4,t} - E(\tilde{e}_{4,t})$$

the model in (3.1) can be redefined as

$$d_t = \tilde{A}_0 + A_1 m_t + A_2 \beta_t + A_3 I^*_t + A_4 d^{**}_t + A_5 p^*_t + A_6 d^+_t + \varepsilon_t,$$

where

$$\varepsilon_t = A_1 e_{4,t} + A_2 e_{5,t}.$$

Hence, $E(\varepsilon_t) = 0$. Determining $E(\tilde{e}_{4,t}\tilde{e}'_{4,t})$, it would then be possible to substitute the observed s_t's and estimate $E(\varepsilon_t \varepsilon'_{t-k})$ in a maximum likelihood procedure similar to those discussed below.

Simplifications can be obtained, however, when $\tilde{s}_t = s_t + c$, where c is a constant indicative of the particular decision-maker's managerial ability, spatial dislocation from the markets of interests, etc. Clearly then, $\tilde{m}_t = m_t + c$, and $\tilde{\beta}_t = \beta_t$. Hence, stochastic problems are not compounded; and estimation procedures are not complicated although some bias results in the constant term.

Stochastic measurement of information also presents considerable problems in estimation. The most reasonable assumption might be

$$\tilde{s}_t = s_t + e_{6,t},$$

where

$$E(e_{6,t}) = 0$$

$$E(e_{6,t}e'_{6,t}) = \begin{cases} \tilde{\Sigma}_6 & \text{for } k = 0, \\ 0 & \text{for } k > 0, \end{cases}$$

and $e_{6,t}$ is the random disturbance in measurement. Hence, this problem would essentially be the same as that presented by stochastic information reception. It then appears that, if an extremely complicated estimation procedure is to be avoided, the $\tilde{s}_t$ used directly by the decision-maker must differ from s_t by no more than a constant associated with that decision-maker.

Estimation When the Number of Information Variables Is Equal to the Number of Decision Variables

In this section a maximum likelihood estimation procedure is derived for the model specified by (3.1) in a special case, and appropriate modifications are made under various stochastic specifications to obtain asymptotic efficiency. As might be expected, the estimation procedure is computationally complicated by the nonlinearities in the subjective parameters. Since both m_t and β_t have associated geometric parameters, a simple reduction such as that used by Koyck (1954) is not possible. The estimation procedure described here then deals directly with the structural version of the model. Dhrymes (1966, 1969, and 1971) has proposed estimation techniques for the structural version of a geometric lag model which can be useful in the development of an estimation procedure for the model presented here. His procedures are, in fact, special cases of the method discussed here applicable when the β_t subjective parameter is identically zero.

Consider the model in (3.1) and a redefinition of parameters and variables as follows:[39]

$$B_o = A_o$$

$$B_1 = \theta \sum_{k=t-t_o}^{\infty} (1-\theta)^{k-t+t_o} A_1 s_{t-k-1} = A_1 m_{t_o}$$

$$B_2 = A_1$$

$$B_3 = (1-\theta) \sum_{k=t-t_o}^{\infty} \phi^{k-t+t_o} A_2 \xi_{t-k-1}$$

$$B_k = A_{k-2} \qquad k = 4, \ldots, 8$$

$$X_o = 1$$

[39] All summations with a lower limit exceeding the upper limit are defined to be zero for ease of exposition.

$$X_{1t}(\theta) = (1 - \theta)^{t - t_o}$$

$$X_{2t}(\theta) = \theta \sum_{k=0}^{t-t_o-1} (1 - \theta)^k s_{t-k-1}$$

$$X_{3t}(\phi) = \phi^{t - t_o}$$

$$X_{4t}(\theta, \phi, m_{t_o}) = (1 - \theta) \sum_{k=0}^{t-t_o-1} \phi^k \xi_{t-k-1}$$

$$X_{5t} = I_t^*$$

$$X_{6t} = d_t^{**}$$

$$X_{7t} = p_t^*$$

$$X_{8t} = d_t^+$$

where

$$\xi_t = \begin{bmatrix} \xi_{t,1,1} \\ \vdots \\ \xi_{t,1,n} \\ \xi_{t,2,2} \\ \vdots \\ \xi_{t,2,n} \\ \xi_{t,3,3} \\ \vdots \\ \xi_{t,n-2,n} \\ \xi_{t,n-1,n-1} \\ \xi_{t,n-1,n} \\ \xi_{t,n,n} \end{bmatrix}$$

$$\begin{aligned} \xi_{t,i,j} &= (s_{t,i} - m_{t,i})(s_{t,j} - m_{t,j}) \\ &= \left[s_{t,i} - \theta \sum_{k=0}^{t-t_o-2} (1 - \theta)^k s_{t-k-2,i} - (1 - \theta)^{t-t_o-1} m_{t_o,i} \right] \\ &\quad \times \left[s_{t,j} - \theta \sum_{k=0}^{t-t_o-2} (1 - \theta)^k s_{t-k-2,j} - (1 - \theta)^{t-t_o-1} m_{t_o,j} \right] \end{aligned}$$

and

$$m_{t_o} = \theta \sum_{k=0}^{\infty} (1 - \theta)^k s_{t_o-k-1}.$$

If the data available for d_t and s_t are for time periods t_o to t_f, then B_1 and B_3 will be fixed throughout the sampling period and can, therefore, be treated as parameters to be estimated since they are indeed unknown. Thus, the effect of prior knowledge at t_o will be estimated in the course of estimation of the other parameters of interest. The variables, $X_{1,t}$, $X_{2,t}$, $X_{3,t}$, and $X_{4,t}$, are specified as dependent on the unknown parameters, θ, ϕ, and m_{t_o}, since only the s_t for $t_o \leq t < t_f$ are observable. To employ the standard notation, let $Y_t = d_t$ so that (3.1) can be rewritten as $Y_t = BX_t + \varepsilon_t$ for $t = t_o, \ldots, t_f$, where $B = [B_o B_1 \ldots B_8]$ and

$$X_t = X_t(\theta,\phi,m_{t_o}) = \begin{bmatrix} X_o \\ X_{1,t}(\theta) \\ X_{2,t}(\theta) \\ X_{3,t}(\theta) \\ X_{4,t}(\theta,\phi,m_{t_o}) \\ X_{5,t} \\ \vdots \\ X_{8,t} \end{bmatrix} \tag{3.10}$$

In a compact multivariate notation, the estimation model then takes the form $Y = X\underline{B} + \varepsilon$ with

$$Y = \begin{bmatrix} Y_{t_o} \\ Y_{t_o+1} \\ \vdots \\ Y_{t_f} \end{bmatrix} \qquad \varepsilon = \begin{bmatrix} \varepsilon_{t_o} \\ \varepsilon_{t_o+1} \\ \vdots \\ \varepsilon_{t_f} \end{bmatrix}$$

$$X = X(\theta,\phi,m_{t_o}) = \begin{bmatrix} I_p \otimes X'_{t_o} \\ I_p \otimes X'_{t_o+1} \\ \vdots \\ I_p \otimes X'_{t_f} \end{bmatrix} \tag{3.11}$$

and

$$\underline{B} = \begin{bmatrix} (B^{1\cdot})' \\ (B^{2\cdot})' \\ \vdots \\ (B^{p\cdot})' \end{bmatrix} \tag{3.12}$$

where $B^{i\cdot}$ is the ith row of B, I_p is a $p \times p$ identity matrix, and $I_p \otimes X'_t$ is the Kronecker (direct) product of I_p and X'_t.

Assuming ε_t is a stochastic disturbance, such as in (3.2), (3.3), (3.4), (3.5), or (3.6), the stochastic specifications for the estimation problem would be

$$\begin{aligned} \varepsilon_t &= \rho\varepsilon_{t-1} + e_t \\ E(e_t) &= 0 \\ E(e_t e'_{t-k}) &= \begin{cases} \tilde{\Sigma} & \text{for } k = 0 \\ 0 & \text{for } k > 0 \end{cases} \end{aligned} \tag{3.13}$$

where ρ is some $p \times p$ diagonal matrix of serial correlation coefficients.

Contemporaneously correlated disturbances. As a first step in the development of a general estimation procedure, consider the assumptions

$$\begin{aligned} E(\varepsilon_t) &= 0 \\ E(\varepsilon_t \varepsilon'_{t-k}) &= \begin{cases} \Sigma & \text{for } k = 0 \\ 0 & \text{for } k > 0 \end{cases} \end{aligned} \tag{3.14}$$

which, in compact notation, can be written[40]

$$E(\varepsilon) = 0,$$

$$E(\varepsilon\varepsilon') = I_T \otimes \Sigma = \Phi,$$

where $T = t_f - t_o + 1$.

When θ, ϕ, and m_{t_o} are known, we would then simply have a classical multivariate regression problem. Assuming normality, $\varepsilon \sim N(O,\Phi)$, the log of the likelihood function is

$$\begin{aligned} L(\underline{B},\Sigma,\theta,\phi,m_{t_o}|Y,s_t) = & -\frac{Tp}{2}\log(2\pi) - \frac{T}{2}\log|\Sigma^{-1}| \\ & -\frac{1}{2}(y - X\underline{B})'\Phi^{-1}(y - X\underline{B}) = -\frac{Tp}{2}\log(2\pi) \qquad (3.15) \\ & -\frac{T}{2}\log|\Sigma^{-1}| - \frac{1}{2}\sum_{t=t_o}^{t_f}(Y_t - BX_t)'\Sigma^{-1}(Y_t - BX_t), \end{aligned}$$

where the presence of s_t denotes all s_t for $t_o \leq t < t_f$. Upon noting the following aspects of the problem, a possible estimation technique suggests itself.

1. Given θ, ϕ, and m_{t_o}, conditional maximum likelihood estimators of $\underline{B}$ and Σ can be obtained through standard regression procedures.
2. The derivation of (1.32) indicates that θ and ϕ must both lie in small intervals. Hence, search techniques could be additionally used to locate the maximum likelihood estimates of θ and ϕ given m_{t_o}.
3. If a reasonable initial estimate of m_{t_o} can be obtained, then estimation of $\underline{B}$ can be used to improve the initial estimate, perhaps in an iterative fashion, since both A_1 and $A_1 m_{t_o}$ are estimated in the estimation of $\underline{B}$.

Following the method indicated above, conditional maximum likelihood estimators of $\underline{B}$ and Σ for given θ, ϕ, and m_{t_o} are found to be (Anderson, 1958; Rao, 1965)

$$\hat{\underline{B}}(\theta,\phi,m_{t_o}) = (X'X)^{-1}X'Y$$

$$\hat{\Sigma}(\theta,\phi,m_{t_o}) = \frac{1}{T}\sum_{t=t_o}^{t_f}(Y_t - \hat{B}X_t)(Y_t - \hat{B}X_t)'$$

assuming $X'X$ is nonsingular and that $\hat{\underline{B}}$ and $\hat{B}$ have the same structures as $\underline{B}$ and B. That is,

$$L[\hat{\underline{B}}(\theta,\phi,m_{t_o}), \hat{\Sigma}(\theta,\phi,m_{t_o})|\theta,\phi,m_{t_o},Y,s_t] = \max_{\underline{B},\Sigma} L(\underline{B},\Sigma|\theta,\phi,m_{t_o},Y,s_t). \qquad (3.17)$$

Dependence on θ, ϕ, and m_{t_o} is specified since X_t and thus X are dependent on these unknown parameters.

For a given m_{t_o}, the likelihood function

$$L(\underline{B},\Sigma,\theta,\phi|m_{t_o},Y,s_t) \qquad (3.18)$$

can then be maximized by choosing a sufficient number of points (θ_i,ϕ_i) in the unit square and selecting $\hat{\theta}(m_{t_o})$ and $\hat{\phi}(m_{t_o})$ such that[41]

[40] The Σ used here in the derivation of the estimation procedure is not to be confused with the Σ associated with the Markov process discussed in the derivation of (1.15).

[41] How densely the unit square must be covered, of course, depends on the accuracy one desires the estimators to possess (assuming that huge spikes in the likelihood function do not elude the search). Empirical applications indicate that computer time is economized by first employing a coarse-grid search. Then various kinds of search techniques, possibly depending on concavity, can be implemented from each of the relative maxima indicated by the course grid approach.

$$L[\underline{\hat{B}}(\hat{\theta},\hat{\phi},m_{t_o}),\ \hat{\Sigma}(\hat{\theta},\hat{\phi},m_{t_o}),\ \hat{\theta}(m_{t_o}),\ \hat{\phi}(m_{t_o})|m_{t_o},Y,s_t]$$

$$= \max_{\substack{\theta_i\in(O,1)\\ \phi_i\in(O,1)}} L[\underline{\hat{B}}(\theta_i,\phi_i,m_{t_o}),\ \hat{\Sigma}(\theta_i,\phi_i,m_{t_o}),\ \theta_i,\phi_i|m_{t_o},Y,s_t]. \tag{3.19}$$

Thus, all that remains is the estimation of m_{t_o}. As indicated above, the method of estimation discussed in this section is iterative and requires an initial estimate of m_{t_o}, denoted as $\hat{m}_{t_o}^{(o)}$, to be used as a starting point for the procedure.[42] Assuming an $\hat{m}_{t_o}^{(o)}$ is chosen, an $X_{4,t}^{(o)}$ can be calculated according to (3.8) using $\hat{m}_{t_o}^{(o)}$ in place of m_{t_o} in (3.9). Maximizing the likelihood function in (3.18) as described in (3.16), (3.17), and (3.19), given $\hat{m}_{t_o}^{(o)}$ and the observed Y and s_t, then produces conditional estimates of $\underline{B}$, Σ, θ, and ϕ, denoted as $\underline{\hat{B}}^{(o)}$, $\hat{\Sigma}^{(o)}$, $\hat{\theta}^{(o)}$, and $\hat{\phi}^{(o)}$, respectively. Maximum likelihood estimates of B_1 and B_2 conditional on $\hat{m}_{t_o}^{(o)}$ are obtainable from $\underline{\hat{B}}^{(o)}$ according to (3.8), (3.10), and (3.12).

The importance of the equality of the number of information variables and the number of decision variables in this estimation method now becomes apparent. If the initial estimate $\hat{m}_{t_o}^{(o)}$ is to have a unique improvement, then $\hat{B}_2^{(o)}$ must be nonsingular implying $n = p$. As is usual in similar stochastic problems, $\hat{B}_2^{(o)}$ will be nonsingular with probability one so that an improved estimate of m_{t_o} might be computed as[43]

$$\hat{m}_{t_o}^{(1)} = [\hat{B}_2^{(o)}]^{-1}\hat{B}_1^{(o)}. \tag{3.20}$$

That is, since $B_1 = A_1 m_{t_o}$ and $B_2 = A_1$, the nonsingularity of A_1 implies $m_{t_o} = B_2^{-1}B_1$ indicating (3.20) as a possibility for improving $\hat{m}_{t_o}^{(o)}$. One can then possibly continue to improve the estimate of m_{t_o} by calculating a new $X_{4,t}^{(1)}$, $\underline{\hat{B}}^{(1)}$ and $\hat{m}_{t_o}^{(2)}$ dependent on $\hat{m}_{t_o}^{(1)}$, etc.

In the case that the contemporaneous correlation matrix is not an identity, estimates might be further improved at each iteration by a method similar to that proposed by Zellner (1962). Noting that the minimum-variance unbiased estimator of $\underline{B}$ is given by Aitken's generalized least-squares estimator,

$$\underline{B} = (X'\Phi^{-1}X)^{-1}X'\Phi^{-1}Y, \tag{3.21}$$

when X and Φ are known, it becomes apparent that more asymptotic efficiency might be gained by substituting consistent estimates of unknown parameters in (3.21). In each iteration we might then estimate

$$\hat{\underline{\hat{B}}}^{(k)} = \{[X^{(k)}]'[\hat{\Phi}^{(k)}]^{-1}X^{(k)}\}^{-1}[X^{(k)}]'[\hat{\Phi}^{(k)}]^{-1}Y \tag{3.22}$$

and

$$\hat{\hat{m}}_{t_o}^{(k+1)} = [\hat{\hat{B}}_2^{(k)}]^{-1}\hat{\hat{B}}_1^{(k)},$$

where $\hat{\Phi}^{(k)} = I_t \otimes \hat{\Sigma}^{(k)}$, taking $\hat{\hat{m}}_{t_o}^{(k+1)}$ as a starting point for the succeeding iteration. A discussion of the properties of the estimators so obtained, however, will be postponed until the stochastic assumptions have been further generalized.

[42] The criterion for choosing the initial m_{t_o} will not be discussed here since the best procedure would depend on the particular aspects and data that might be peculiar to any one problem. For example, if data on the s_t are available for several periods prior to t_o, then a geometrically weighted average (using the appropriate value of θ) of those s_t with a normalized total weighting might serve as an $\hat{m}_{t_o}^{(o)}$. If such data are not available, then some kind of average of the first several observations on s_t might suffice.

[43] Of course, if $p > n$, then one might estimate m_{t_o} at this point by computing a least-squares estimator of m_{t_o} for

$$B_1^{(o)} = B_2^{(o)} m_{t_o},$$

but the more practical case where $p < n$ can still not be handled with this method.

Serially and contemporaneously correlated disturbances. If we revise the assumption (3.14) to (3.13) and consider the possibility of serial correlation, little revision is needed in the above estimation method. Parks (1967) has proposed a method for more efficient estimation of $\underline{B}$ when X is known and both serial and contemporaneous correlation exist. The only modification in the above procedure would be the implementation of Parks' method at each iteration. Following Parks, the initial disturbance can be written as

$$\varepsilon_{t_o,i} = (1 - \rho_i^2)^{-1/2} e_{t_o,i}$$

(where the i subscript denotes the ith element of the respective disturbance vectors except in the case of ρ_i which denotes the ith diagonal coordinate of ρ) so that the initial disturbance has the same variance as subsequent disturbances when

$$\varepsilon_{t,i} = \rho_i \varepsilon_{t-1,i} + e_{t,i} \qquad \text{for } t = t_o + 1, \ldots, t_f.$$

Letting

$$P = \begin{bmatrix} (I_p - \rho^2)^{-1/2} & 0 & 0 & \ldots 0 \\ \rho(I_p - \rho^2)^{-1/2} & I_p & 0 & \ldots 0 \\ \rho^2(I_p - \rho^2)^{-1/2} & \rho & I_p & \ldots 0 \\ \vdots & \vdots & \vdots & \vdots \\ \rho^{T-1}(I_p - \rho^2)^{-1/2} & \rho^{T-2} & \rho^{T-3} & \ldots I_p \end{bmatrix} \tag{3.23}$$

where ρ^j and $(I_p - \rho^2)^{-1/2}$ are diagonal matrices with respective diagonal elements $(\rho_i)^j$ and $[1 - (\rho_i)^2]^{-1/2}$, we can simply write $\varepsilon = Pe$, where

$$e = \begin{bmatrix} e_{t_o} \\ e_{t_o+1} \\ \vdots \\ e_{t_f} \end{bmatrix}$$

and

$$E(e) = 0$$

$$E(ee') = I_T \otimes \tilde{\Sigma}.$$

In terms of the basic model, the covariance structure then becomes

$$E(\varepsilon\varepsilon') = E(Pee'P') = P(I_T \otimes \tilde{\Sigma})P' = \Phi.$$

Continuing to follow Parks' method, we would then compute $\hat{B}^{(k)}$, $\hat{\theta}^{(k)}$, and $\hat{\phi}^{(k)}$ according to (3.16) and (3.19) at each iteration k. Hence, the disturbances are estimated by

$$\hat{\varepsilon}_t^{(k)} = Y_t - \hat{B}^{(k)} X_t \qquad t = t_o, \ldots, t_f$$

so that the correlation coefficients are estimated by

$$\hat{\rho}_i = \frac{\sum_{t=t_o+1}^{t_f} \hat{\varepsilon}_{t,i}^{(k)} \hat{\varepsilon}_{t-1,i}^{(k)}}{\sum_{t=t_o+1}^{t_f} [\hat{\varepsilon}_{t-1,i}^{(k)}]^2}, \tag{3.24}$$

where $\hat{\varepsilon}_{t,i}^{(k)}$ is the ith element of $\varepsilon_t^{(k)}$. The estimated ρ_i's are then substituted in (3.23) to obtain an estimate $\hat{P}^{(k)}$ of P. Premultiplying $Y = X\hat{B} + \hat{\varepsilon}$ by $[\hat{P}^{(k)}]^{-1}$ would thus obtain $\hat{e}^{(k)} = \hat{Y}^* + X^*\hat{B}$, where $\hat{Y}^* = [\hat{P}^{(k)}]^{-1} Y$ and $X^* = [\hat{P}^{(k)}]^{-1} X^{(k)}$. Hence, $\tilde{\Sigma}$ can be estimated by

$$\hat{\hat{\Sigma}}^{(k)} = \frac{1}{T} \sum_{j=1}^{T} \hat{e}_t' \hat{e}_t \tag{3.25}$$

where $\hat{e}_t$ is related to $\hat{e}$ in exactly the same way as ε_t is related to ε. The original covariance matrix Φ would then be estimated by

$$\hat{\hat{\Phi}}^{(k)} = \hat{P}^{(k)}[I_T \otimes \hat{\hat{\Sigma}}^{(k)}]\hat{P}^{(k)\prime}$$

so that the estimator in (3.22) would become

$$\underline{\hat{\hat{B}}}^{(k)} = \{[X^{(k)}]'[\hat{\hat{\Phi}}^{(k)}]^{-1} X^{(k)}\}^{-1}[X^{(k)}]'[\hat{\hat{\Phi}}^{(k)}]^{-1} Y.$$

Thus, we can again compute as a starting point for the succeeding iteration

$$\hat{\hat{m}}_t^{(k+1)} = [\hat{\hat{B}}_2^{(k)}]^{-1} \hat{\hat{B}}_1^{(k)}$$

since $\hat{\hat{B}}_2^{(k)}$ will be nonsingular with probability one.

Properties of the estimators. If $\hat{m}_{t_o}^{(o)}$ is sufficiently close to m_{t_o} and the sequence $\hat{\hat{m}}_{t_o}^{(o)}, \hat{\hat{m}}_{t_o}^{(1)}, \ldots,$ converges to a finite limit, then

$$\hat{\hat{B}}^{(\infty)} = \lim_{k \to \infty} \underline{\hat{\hat{B}}}^{(k)}$$

$$\hat{\hat{\Phi}}^{(\infty)} = \lim_{k \to \infty} \hat{\hat{\Phi}}^{(k)}$$

$$\hat{\theta}^{(\infty)} = \lim_{k \to \infty} \hat{\theta}^{(k)}$$

and

$$\hat{\phi}^{(\infty)} = \lim_{k \to \infty} \hat{\phi}^{(k)}$$

exist and are consistent estimators of $\underline{B}$, Φ, θ, and ϕ, respectively.[44] The proof of this statement is rather straightforward, assuming $\hat{m}_{t_o}^{(o)}$ has been chosen sufficiently close to m_{t_o} so that $\hat{\hat{m}}_{t_o}^{(k)}$ converges to m_{t_o}. The argument given here will then be informal and will appeal to several results which are already in the literature. From (3.19), it is clear that, if $\hat{\hat{m}}_{t_o}^{(k)}$ converges to a finite limit, $\underline{\hat{B}}^{(k)}$, $\hat{\Sigma}^{(k)}$, $\hat{\theta}^{(k)}$, and $\hat{\phi}^{(k)}$ will also since Y and s_t are regarded as fixed. Thus, when serial correlation is not present, $\hat{\hat{\Phi}}^{(k)}$ simply depends on $\hat{\Sigma}^{(k)}$ and, hence, $\underline{\hat{\hat{B}}}^{(k)}$ will also converge to a finite limit for fixed Y and s_t. Likewise in the case of serial correlation, it is immediate that all the $\hat{\rho}_i$'s and, hence, $\hat{P}^{(k)}$, $[\hat{P}^{(k)}]^{-1}$, $\hat{\hat{\Sigma}}^{(k)}$, and $\underline{\hat{\hat{B}}}^{(k)}$ will converge to a finite limit for fixed Y and s_t.

Proceeding with the proof of consistency then, it is well known that, in the case of serial correlation, $\hat{P}^{(\infty)}$ is a consistent estimator of P when X is given since $\hat{\rho}_i$ consistently estimates ρ_i. Also, by invoking Slutsky's theorem (Cramer, 1946) it has been shown, for example, by Parks (1967), that $\hat{\hat{\Sigma}}^{(\infty)}$ consistently estimates Σ for a given X; thus, $\hat{\hat{\Phi}}^{(\infty)}$ is consistent for Φ when X is given. Of course, $[\hat{\hat{\Phi}}^{(\infty)}]^{-1}$ consistently estimates Φ^{-1} so that $\underline{\hat{\hat{B}}}^{(\infty)}$ is also consistent when X is given. Furthermore, all of the above arguments continue to hold when X is replaced by a consistent estimator of X. Because X is estimated solely on the basis of $\hat{\theta}^{(\infty)}$, $\hat{\phi}^{(\infty)}$, $\hat{\hat{m}}_{t_o}^{(\infty)}$, and s_t, where s_t is given, all that remains is the proof of consistency for $\hat{\theta}^{(\infty)}$ and $\hat{\phi}^{(\infty)}$. But it is obvious that $\hat{\theta}^{(\infty)}$ and $\hat{\phi}^{(\infty)}$ have been chosen so as to attain the global maximum of the likelihood function. Thus, with some tedious verification of conditions which

[44] Of course, this statement is weak with respect to $\hat{m}_{t_o}^{(o)}$, since $\hat{m}_{t_o}^{(o)}$ may need to be essentially equal to m_{t_o} before the desired convergence occurs.

is omitted here, it is possible to invoke the theorem given by Wald (1949) which proves the consistency of globally maximizing roots of the likelihood function. Actually, Wald's theorem can also be used to establish the consistency of the estimator for m_{t_o} in the generally applicable procedure presented below. Since the estimator for m_{t_o} in the historical-data procedure (also below) is also consistent, the consistency of all estimators will become apparent for the latter two methods without relying on the very weak assumption relating to the convergence of $\hat{\hat{m}}_{t_o}^{(k)}$.

Wald's theorem can also be used to prove the consistency of $\hat{\underline{B}}^{(\infty)}$ regardless of the stochastic assumptions which have been discussed. However, $\hat{\underline{B}}^{(\infty)}$ will in general be asymptotically less efficient than $\hat{\hat{\underline{B}}}^{(\infty)}$ since, based on the consistency of $\hat{\hat{\Phi}}^{(\infty)}$, $\hat{\theta}^{(\infty)}$, and $\hat{\phi}^{(\infty)}$, the asymptotic distribution of $\hat{\hat{\underline{B}}}^{(\infty)}$ is the same as $\hat{\hat{\underline{B}}}^{*}$, where $\hat{\hat{\underline{B}}}^{*}$ is the Aitken's estimator,[45]

$$\hat{\hat{\underline{B}}}^{*} = (X'\Phi^{-1}X)^{-1}X'\Phi^{-1}Y.$$

Thus, $\hat{\hat{\underline{B}}}^{(\infty)}$ is also asymptotically unbiased and efficient in the sense that the Rao-Cramer lower bound is attained. The asymptotic distribution of $\hat{\underline{B}}^{(\infty)}$ is the same as $\hat{\underline{B}}$, where $\hat{\underline{B}} = (X'X)^{-1}X'Y$, which is a relatively inefficient estimator except when disturbances are uncorrelated.

A Generally Applicable Procedure

In this section a procedure applicable when the number of information variables exceeds the number of decision variables is briefly discussed. The procedure is an obvious extension of the one discussed above and, although the iterative aspects of the procedure are eliminated, the dimension of the likelihood search is increased. Since initial estimates can no longer be improved when A_1 is oversquare, that is, when $n > p$, it becomes necessary also to search for the maximum likelihood estimator of m_{t_o}. Although the parametric space for m_{t_o} is not as small as the space for θ and ϕ, it should be possible to confine the most dense part of the search to a perhaps manageable region of the space. Supposedly, m_{t_o} is a subjective estimate of s_{t_o}. Thus, if the variability of observed phenomena around subjective expectations is not great, the likelihood search might be essentially confined to a relatively small neighborhood of s_{t_o}.

Suppose some source of information allows us to determine that m_{t_o} lies in some neighborhood $N(s_{t_o})$ of s_{t_o}. For a given θ, ϕ, and m_{t_o}, conditional maximum likelihood estimators are again given by (3.16). By choosing a sufficient number of points (θ_i,ϕ_i) in the unit square and $m_{t_o,j}$ in $N(s_{t_o})$, maximum likelihood estimators $\hat{\theta}$, $\hat{\phi}$, and $\hat{m}_{t_o}$ would be found as

$$L[\hat{\underline{B}}(\hat{\theta},\hat{\phi},m_{t_o}), \hat{\Sigma}(\hat{\theta},\hat{\phi},m_{t_o}), \hat{\theta},\hat{\phi},m_{t_o}|Y,s_t]$$
$$= \max_{\substack{\theta_i\in(0,1)\\ \phi_i\in(0,1)\\ m_{t_o,j}\in N(s_{t_o})}} [\hat{\underline{B}}(\theta_i,\phi_i,m_{t_o,j}), \hat{\Sigma}(\theta_i,\phi_i,m_{t_o,j}), \theta_i,\phi_i,m_{t_o,j}|Y,s_t].$$

Obviously, this method becomes quite tedious and rapidly becomes computationally infeasible as n, the number of information variables, increases. The estimators so obtained, however, can be shown to have the same properties as those in (3.19). Modifications can also be made according to the Zellner or Parks method, depending on the stochastic assumptions, to obtain an asymptotically efficient estimator of $\underline{B}$.

[45] See Zellner (1962) for a more detailed discussion of the asymptotic distribution theory associated with these estimators.

A General Procedure When Historical Data Are Available

Although neither of the estimation techniques discussed above are computationally appealing, a more simplified method can possibly be used when historical information variable data are available. Both the need for iteration and searching on m_{t_o} can be eliminated thus allowing computational feasibility as well as general applicability.

Consider the period of applicability of the econometric model to be t_h to t_f and a partition of that period into two periods, t_h to $t_o - 1$ and t_o to $t_f (t_h < t_o < t_f)$. Suppose data are available on s_t for $t = t_h, \ldots, t_f$ and on Y_t (or d_t) for $t = t_o, \ldots, t_f$. We can then consider estimating m_{t_o} by

$$\hat{m}_{t_o}(\theta) = c(t_o - t_h)\theta \sum_{k=0}^{t_o - t_h} (1 - \theta)^k s_{t_o - k - 1}, \tag{3.26}$$

where $c(t_o - t_h)$ is chosen to give a normalized total weighting to the s_t, $t = t_h, \ldots, t_o - 1$, i.e.,[46]

$$c(t_o - t_h) = \left[\theta \sum_{k=0}^{t_o - t_h} (1 - \theta)^k \right]^{-1}.$$

Hence, it is immediate that $\hat{m}_{t_o}(\theta)$ will be a consistent estimator of m_{t_o} even when a consistent estimator of θ is substituted in (3.26) if we consider $T = t_f - t_h + 1 \to \infty$ in such a way that both $T_1 = t_o - t_h \to \infty$ and $T_2 = t_f - t_o + 1 \to \infty$ when establishing consistency.

The estimation procedure would then be as follows: First, a sufficient number of points (θ_i, ϕ_i) are chosen from the unit square so that the global maximum of the likelihood function with respect to θ and ϕ can be located. For each point (θ_i, ϕ_i), we then estimate m_{t_o} by $\hat{m}_{t_o}(\theta_i)$ and $\underline{B}$ by

$$\hat{\underline{B}}[\theta_i, \phi_i, \hat{m}_{t_o}(\theta_i)] = (X'X)^{-1} X'Y \tag{3.27}$$

where X depends on θ_i, ϕ_i, and $\hat{m}_{t_o}(\theta_i)$ according to (3.8), (3.10), and (3.11). In the case of serially uncorrelated disturbances, i.e., where $\Phi = I_T \otimes \Sigma$, Σ would be estimated by

$$\hat{\Sigma}[\theta_i, \phi_i, \hat{m}_{t_o}(\theta_i)] = \frac{1}{T_2} \sum_{t=t_o}^{t_f} (Y_t - \hat{B}X_t)(Y_t - \hat{B}X_t)' \tag{3.28}$$

where Y_t, $\hat{B}$, and X_t are related to Y, $\hat{\underline{B}}$, and X as in (3.11) and (3.12). Maximum likelihood estimators $\hat{\theta}$ and $\hat{\phi}$ are then chosen such that

$$\begin{aligned} &L\{\hat{\underline{B}}[\hat{\theta}, \hat{\phi}, \hat{m}_{t_o}(\hat{\theta})], \hat{\Sigma}[\hat{\theta}, \hat{\phi}, \hat{m}_{t_o}(\hat{\theta})], \hat{\theta}, \hat{\phi}, \hat{m}_{t_o}(\hat{\theta}) \mid Y, s_t\} \\ &\quad = \max_{\substack{\theta_i \in (0,1) \\ \phi_i \in (0,1)}} L\{\hat{\underline{B}}[\theta_i, \phi_i, \hat{m}_{t_o}(\theta_i)], \hat{\Sigma}[\theta_i, \phi_i, \hat{m}_{t_o}(\theta_i)], \theta_i, \phi_i, \hat{m}_{t_o}(\theta_i) \mid Y, s_t\} \end{aligned} \tag{3.29}$$

Again, an asymptotically efficient estimator of $\underline{B}$ can be computed as

$$\hat{\hat{\underline{B}}} = (X'\hat{\Phi}^{-1}X)^{-1} X'\hat{\Phi}^{-1} Y, \qquad \text{where} \qquad \hat{\Phi} = I_T \otimes \hat{\Sigma}[\hat{\theta}, \hat{\phi}, \hat{m}_{t_o}(\hat{\theta})].$$

---

[46] Of course,

$$\lim_{t_h \to -\infty} \hat{m}_{t_o}(\theta) = m_{t_o}$$

for all $c(t_o - t_h)$ such that

$$\lim_{t_h \to -\infty} c(t_o - t_h) = 1.$$

However, $c(t_o - t_h)$ is chosen here in an obvious way to provide a better estimate of m_{t_o} in a small sample situation.

If serial correlation is present, then we can estimate the ρ_i's as in (3.24) and thus substituting into (3.23), a consistent estimator of P can be obtained. Estimating $\tilde{\Sigma}$ as in (3.25), an asymptotically efficient estimator of $\underline{B}$ can be computed as

$$\hat{\underline{\hat{B}}} = (X'\hat{\hat{\Phi}}^{-1}X)^{-1}X'\hat{\hat{\Phi}}^{-1}Y, \qquad \text{where} \qquad \hat{\hat{\Phi}} = \hat{P}(I_T \otimes \hat{\tilde{\Sigma}})\hat{P}'.$$

Clearly, by the proof given in the preceding sections, all of the estimators obtained by this method are also consistent since $\hat{m}_{t_0}(\theta)$ is consistent. The estimator $\hat{\underline{\hat{B}}}$ corresponding to the Zellner or Parks methods, as the case may be, is again asymptotically unbiased and efficient by the same argument and has the same asymptotic distribution as $\hat{\underline{\hat{B}}}^*$, where $\hat{\underline{\hat{B}}}^*$ is the Aitken's generalized least-squares estimator, $\hat{\underline{\hat{B}}}^* = (X'\Phi^{-1}X)^{-1}X'\Phi^{-1}Y$.

Further Possible Simplifications

Returning to the derivation of (1.32), it appears that the likelihood search procedures discussed above can possibly be further simplified under certain assumptions. If the temporal lag distributions used in formulating the parameters of the subjective distributions are identical, i.e., $\phi = (1 - \theta)$, then estimation could be highly simplified since only a one-dimensional likelihood search in the unit interval would be required when historical data are available. Furthermore, since both geometric parameters of the resulting model are then equal, a reduced form of (1.32) in the linear case can be obtained as

$$d_t = (1 - \theta)d_{t-1} + \theta A_o + \theta A_1 s_{t-1} + (1 - \theta)^2 A_2 \xi_{t-1}. \tag{3.30}$$

Although (3.30) would still be a cumbersome model for estimation purposes, the number of parameters that would have to be estimated in any standard regression program would be reduced somewhat since the infinite sums are no longer split. A one-dimensional search on θ would still be necessary, however, due to the presence of m_t in ξ_{t-1}.

5 SUPPLY RESPONSE IN THE CALIFORNIA FIELD CROP SECTOR

The most general version of the decision model corresponding to (2.27) might be summarized as follows:

$$d_{tj} = A_{oj} + A_{1j}.m_t + A_{2j}.\beta_t + A_{3j}.I_t^* + A_{4j}.d_t^{**} + A_{5j}.p_t^* + A_{6j}d_{tj}^+ + \varepsilon_{tj}$$

where

d_{tj} = jth decision variable
m_t = vector of prior subjective means for the econometric information variables of interest
β_t = vector of prior subjective variances and covariances for the information variables of interest
I_t^* = vector of indicator variables times participation rates for the various allotment programs
d_t^{**} = vector of allotment levels times participation rates for the various allotments
p_t^* = vector of price-support levels times the rates of participation when voluntary for the various programs
d_{tj}^+ = level of diversion associated with the jth decision variable

and

ε_{tj} = stochastic disturbance in the jth decision correspondence.

In each case the A's represent unknown coefficient vectors and matrices of appropriate dimensions.

Having now derived this general model for supply response investigation, attention can be turned to the identification of important forces operative in the California field crop sector itself. The important decision variables describing supply response, as well as the information variables of interest in the decision-making process, should then become apparent.

Government Programs and Policy in the Field Crop Sector[47]

Apparently, the major forces affecting the important California field crops in the last 20 years have been the allotments, marketing quotas, price-support programs, and diversion possibilities set up by the various farm commodity programs. Beginning with the Agricultural Adjustment Act of 1933, the Secretary of Agriculture was given far-reaching powers in the control of agricultural prices and production. Although the Commodity Credit Corporation (CCC) was not an integral part of the program between 1933 and 1938, the Agricultural Adjustment Act of 1938 placed more emphasis on price-support loans by the CCC and on the integration of the activities of the CCC with acreage allotments and marketing quotas. Under the Act and subsequent amending acts, acreage allotments based on historical acreages have been instituted for several field crops. Quotas have been imposed additionally when approval by at least two-thirds of the producers involved has been obtained. Price-support levels have been announced prior to planting, and provision of price-support loans is then made contingent upon compliance with acreage allotments or marketing quotas. Price-support levels determined according to procedures specified by federal legislation are administered by the CCC through direct purchases of surplus production and nonrecourse loans to producers. Quotas have been enforced additionally by the imposition of a heavy tax on the amounts marketed in excess of the quota.

Legislation passed between 1938 and 1961 did little to change the provisions of the 1938 Act, except that the level of price support measured in terms of parity was varied to some extent depending on the strength of the market and the administration in power. Beginning with the emergency Feed Grain Act in 1961, however, diversion possibilities were also established for some crops whereby price support was made provisional on compliance with voluntary allotments reduced by some minimum diversion requirement. Additional diversion payments were then made available for diversion above the minimum requirement, depending on normal farm yield and prevailing price-support level. Although feed-grain programs originally pertained only to corn and grain sorghum, barley was also included for 1962–1966, 1969, and 1970. Diversion possibilities were then also established for wheat and cotton through parts of the 1960's, beginning with wheat in 1962 and cotton in 1966.

Apparently, the most restrictive controls in California have been cotton and rice allotments and marketing quotas. Allotments and quotas have been in effect for cotton since 1954 and for rice since 1955, and have appeared to dominate almost entirely the acreage response of those crops in California. Although allotments have also been established annually for wheat since 1954, marketing quotas were discontinued in 1964. Furthermore, the wheat program has been less restrictive than other allotment programs in some parts of California since wheat is not the most profitable production alternative. When marketing quotas were dropped in 1964, wheat acreage in California was already well below allotment levels. The feed grain

[47] The discussion of government programs given here is indeed very brief. For a more detailed account see Tweeten (1970).

acreage controls have been quite a different story as no sizable decline in acreage plantings took place with the imposition of voluntary allotments. Rather, the production of feed grains in California has continued to expand well above preallotment levels even though a significant proportion of growers have complied and thus received program benefits.

As indicated in the Introduction, the administration of these programs has become increasingly and possibly excessively expensive in recent years. Furthermore, it is not at all apparent upon casual observation of the industry that some of the programs have been successful in attaining the goals set out by public policy. Indeed, the programs have been an important controversial issue at the national level for the last several decades. Hence, major emphasis in the analysis of supply response will be placed on the determination of government commodity program impact. Only then will it be possible to evaluate objectively the effects of the costly programs. In the descriptive study that follows, then, we will be concerned with the identification of competing groups of crops and other factors of importance in California field crop supply response. The estimation of both the direct effects of the government programs and the indirect consequences on the supply response of other crops will then become possible.

Field Crop Supply Response and the Role of Government Programs: An Overview

All of the major California field crops with the exception of alfalfa hay are grown on an annual basis. Furthermore, because agronomic reasons associated with pest control and soil conditioning dictate certain crop rotational patterns, farmers are equipped to grow very different kinds of crops on any piece of land from one year to the next. As a recent study indicates, however, the importance of a rotational cycle lies in taking land out of production of a specific crop as opposed to planting another specified commodity (Shumway *et al.*, 1970). Following a crop with a different crop affected by different diseases and pests helps bring crop diseases under control and breaks pest cycles. Irrigated soil benefits structurally through aeration and granulation if an irrigated crop is followed by a nonirrigated crop. All these factors create a tendency toward high rotational flexibility, and ultimately result in a high potential for annual field crop acreage response and an acute interrelationship in supply among a large number of crops. Thus, analysis of supply in this study can be more easily approached if the state is broken down into smaller districts in which interrelationships can be more easily identified as the subset of competing crops is reduced. For the purpose of this study, the crop-reporting districts used by the California Crop and Livestock Reporting Service provide a useful delineation (fig. 1).[48]

San Joaquin Valley. The San Joaquin Valley has been dominated largely by the production of cotton, alfalfa, and barley, with acreages ranging well above 500,000 each in recent years. About 90 per cent of the state's cotton (California's most important field crop) is produced in the San Joaquin Valley. However, the San Joaquin Valley is a major producer of nearly every important California field crop as corn, grain sorghum, dry edible beans, safflower, sugar beets, and wheat reached acreages in excess of 100,000 in the last several years. Among fruit, nut, or vegetable crops in the Valley, only grapes have exceeded 100,000 acres; and, although grape production has occupied nearly 400,000 acres, the perennial nature of the crop reduces its

[48] Although a more complete breakdown according to soil and climatic features would be more desirable, the availability of data for the statistical investigation will not permit it. Many of the counties in California lie in more than one climatic region (Shumway *et al.*, 1970). However, since many districts can be broken into three or four county groups where almost disjoint subsets of crops compete, a more detailed breakdown would probably not be much more revealing unless county lines were crossed.

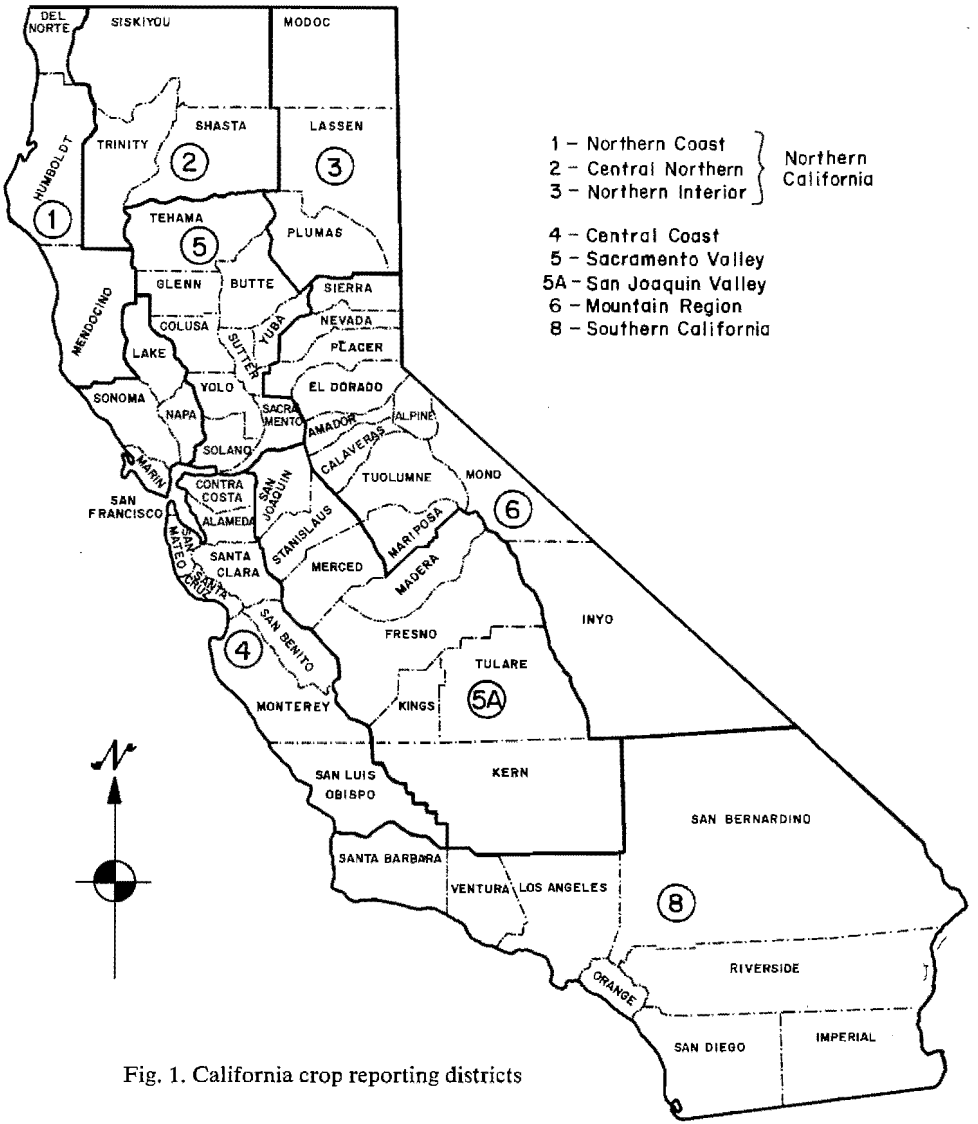

Fig. 1. California crop reporting districts

importance as a possible factor affecting year-to-year acreage decisions. Thus, field crops can be considered as an independent crop group in the analysis of annual supply response.

The cotton program has apparently been the most important force affecting field crop production in the San Joaquin Valley during the last two decades. With the curtailment of foreign production and high domestic support prices during the late 1940's, irrigated cotton land was developed on the west side of the Valley, thus causing acreage to triple. Although the CCC, which handles the administration of the government program price-support activities, had closed out nearly all of its inventories by 1948, the high level of price support and record yields caused heavy carryovers and renewed buildup of excess stocks by the CCC. This situation led to the imposition of acreage controls in 1950. The resulting sharp reduction of acreage, coupled with

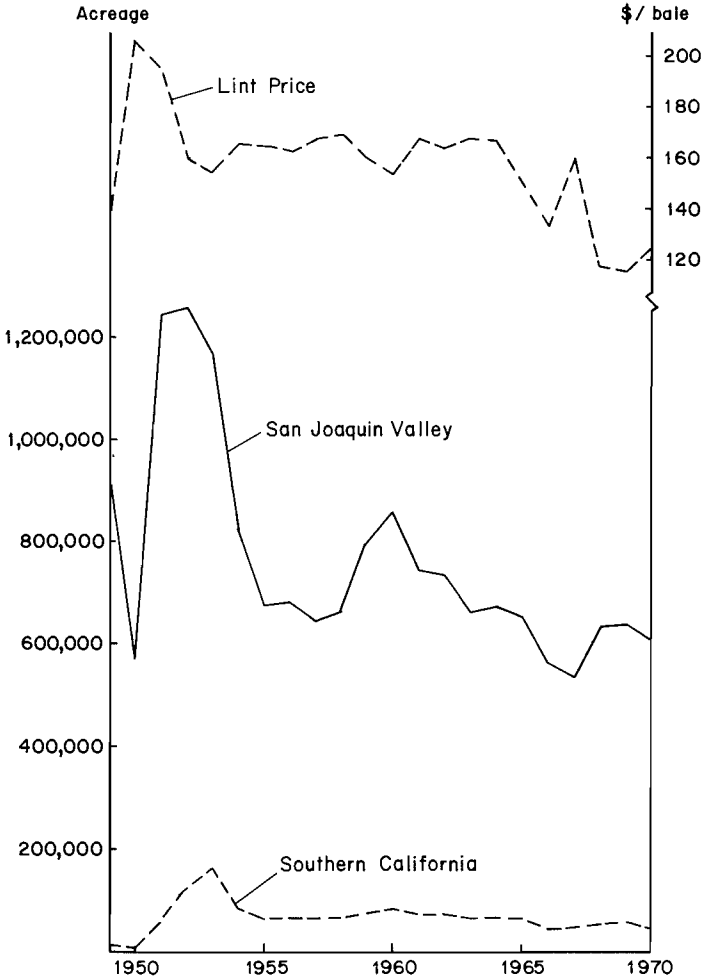

Fig. 2. Cotton acreage and price in California

lower yields in the South and increased demand, led to a severe shortage and an all-time high in cotton prices (fig. 2). Restricting controls were abandoned in 1951, and the San Joaquin Valley acreage soared from less than 600,000 to over 1.2 million acres. Government stocks once again started to accumulate, and by 1954 strict acreage and marketing controls were again imposed. Since 1954, the CCC policies have been more stabilizing, but the acute responsiveness of acreage indicates their importance.

Repercussions of the variation in cotton controls are also evident in the acreage response of all the other field crops produced largely in the southern part of the Valley (Fresno, Kern, Kings, and Tulare counties) except wheat. The acreages of alfalfa, barley, corn, grain sorghum, and sugar beets all show sizable increases when cotton allotments were imposed (figs. 3, 4, 5, 6, and 7). Barley accounted for the most significant initial increases in low-return crop acreages as cotton acreage contracted. Barley had traditionally been more profitable than corn or grain sorghum in California. However, as higher yielding hybrid varieties of corn and sorghum were introduced in the mid-1950's, a sharp expansion of those crops again took place.

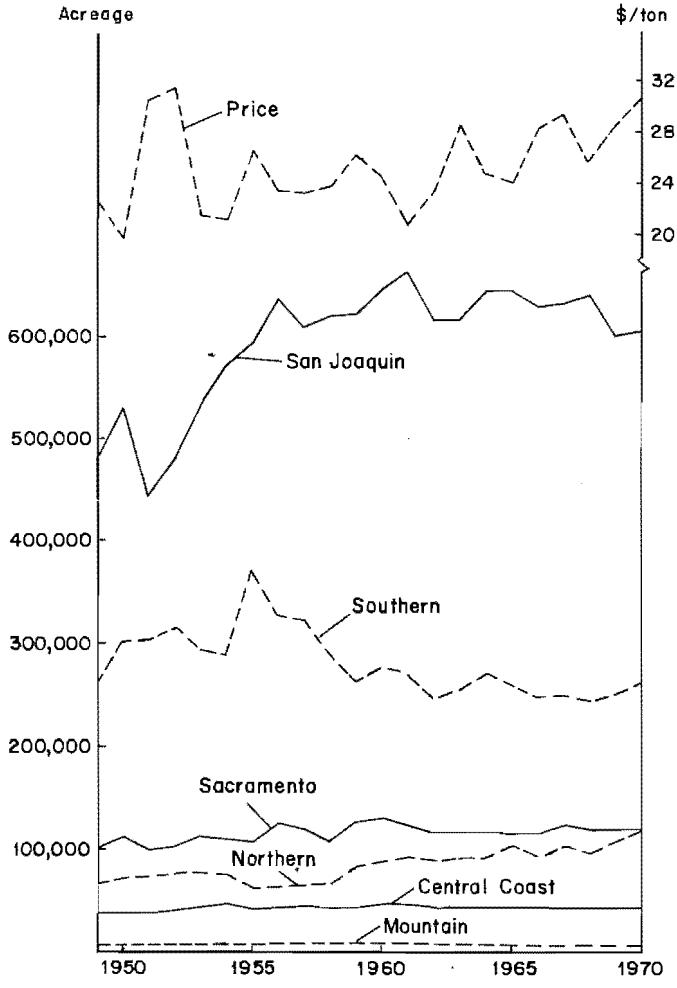

Fig. 3. Alfalfa hay acreage and price in California

Feed grain acreages then declined again in the late 1950's as cotton allotments were boosted and feed prices fell. Then, when it was demonstrated that proper management could produce high safflower yields on irrigated land, the reduction in cotton allotments in the early 1960's led to substantial increases in safflower acreage rather than corn or sorghum. The rapid expansion was halted, though, as producers realized safflower's lack of resistance to verticillium wilt common in cotton and, thus, its lack of characteristics desirable in a rotational crop. Further improved varieties then caused a second rapid expansion of sorghum, beginning in 1961, and corn, beginning in 1963, as cotton allotments continued to be cut.

Although wheat was faced by the same allotment pattern as cotton in the 1950's, only a relatively small acreage was occupied as wheat was not profitable enough to compete with high-return crops for irrigated land. Thus, the wheat program cannot be held responsible for the acreage variation of other crops in the southern part of the Valley. Furthermore, wheat acreage shows no dramatic decline with the imposition of allotments in 1954 or increase in 1964 when compliance was made voluntary

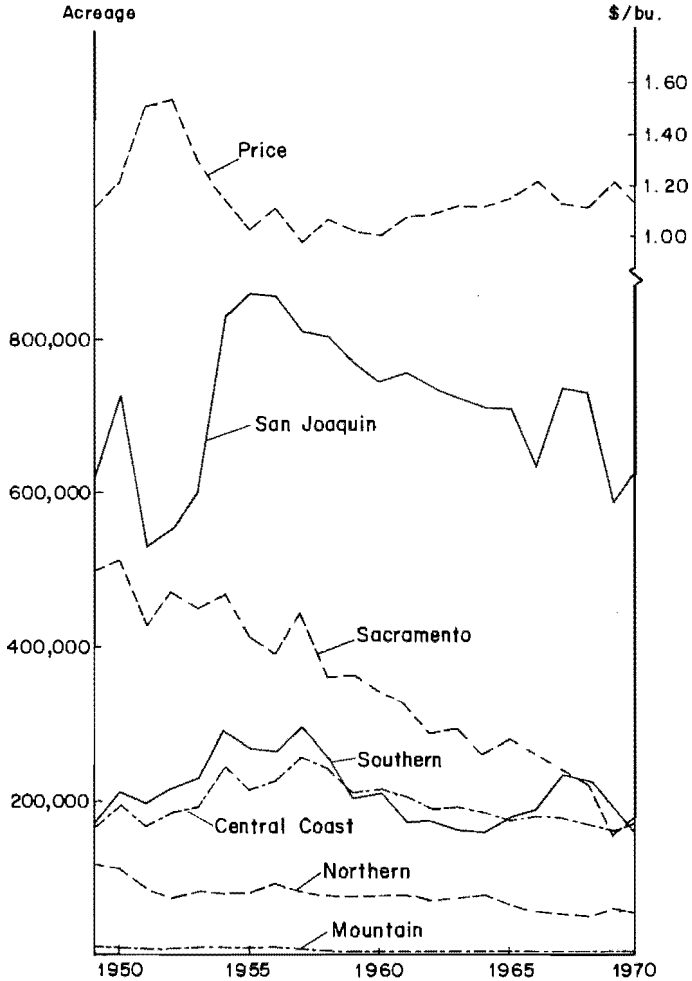

Fig. 4. Barley acreage and price in California

(fig. 8). The most significant change in wheat acreage has been due to the shift toward Mexican wheat varieties beginning essentially in 1969. Wheat acreage in the San Joaquin Valley jumped more than 60 percent from 1969 to 1970 due mainly to expansion in Mexican varieties (fig. 8).

Although about 10 per cent of the state's rice has been produced in the San Joaquin Valley, principally in Fresno County, the repercussions of rice controls in the Valley have been negligible since rice acreage is very small relative to the other crops (fig. 9). Voluntary acreage-control programs for feed grains were also established in the 1960's but with no apparent effect since feed grain acreage tended to rise during the decade.

Sugar beet production has also faced government acreage controls through parts of the last 20 years. Proportionate shares imposed in 1955 through 1960, 1965, and 1966 apparently had more influence in the San Joaquin Valley than in any other area in the state, probably because historical acreage (used in calculating proportionate shares) was relatively low (fig. 7). The San Joaquin Delta area (San Joaquin and

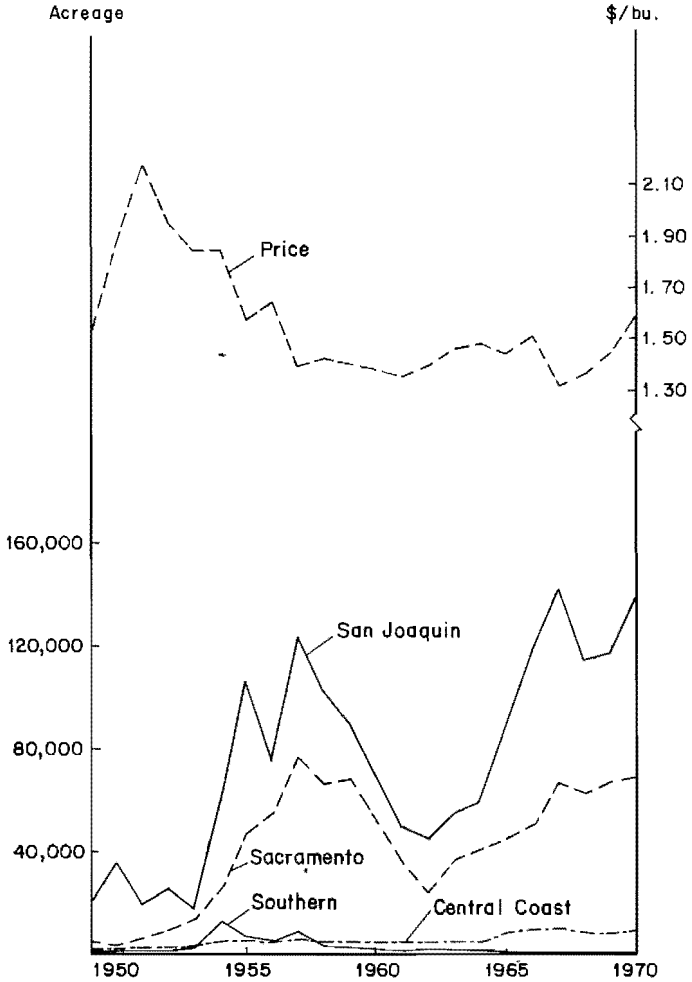

Fig. 5. Corn acreage and price in California

parts of Stanislaus counties) had been the most important sugar beet-producing area in the Valley until cotton allotments were imposed in 1954. Thus, with historical acreages being small in the cotton area, proportionate shares caused San Joaquin Valley sugar beet production to be cut back almost to previous levels. With the removal of proportionate shares in 1961, acreage in the cotton areas again increased; and, as a result of a new processing plant being put into operation at Mendota, the acreage in Fresno, Kern, and Tulare counties jumped another 35,000 acres by 1964. Proportionate shares in later years were not as restricting and were finally discontinued when plantings fell below allotted acreage.

Topographic features of the land and development of irrigation facilities have been major determinants of the spatial distribution of acreage. The heavily irrigated flatlands in the central part of the Valley are influenced largely by high-return crops like cotton, alfalfa, sugar beets, and rice which are virtually entirely irrigated, with other crops being grown mainly for rotational or water availability reasons or as a result of government program regulation.

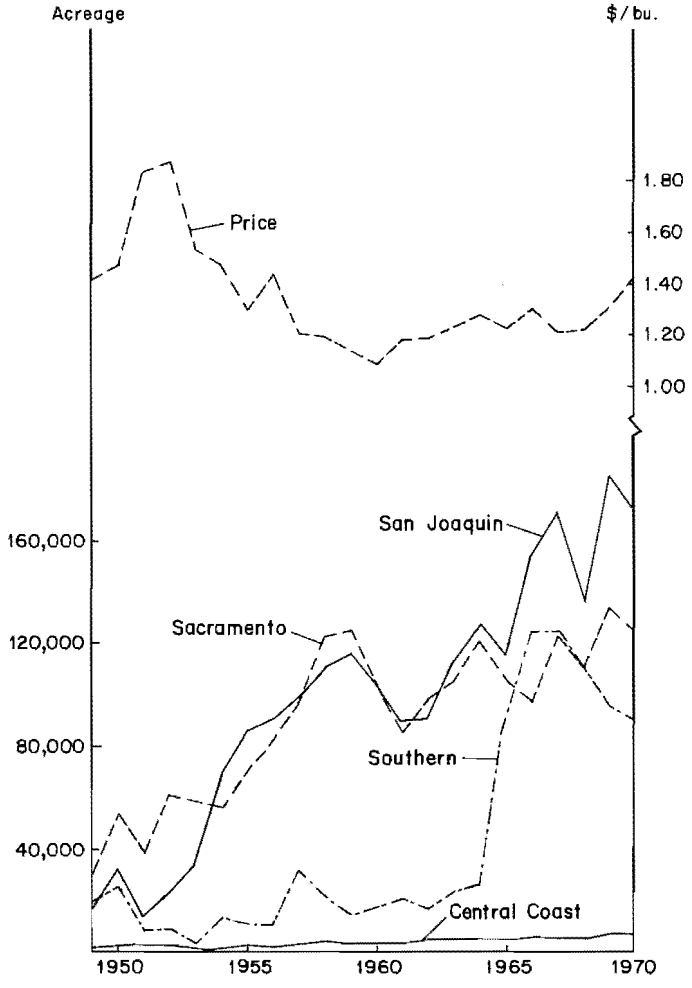

Fig. 6. Grain sorghum acreage and price in California

Dryland farming in the foothills around the Valley has been largely dominated by barley and wheat while accounting for most of the oat production. Wheat has been grown chiefly on the eastern side of Kern and Tulare counties, while barley has been raised mainly on the west side of the Valley. Some of barley's dominance on the west side, however, will be lost as new lands are brought into irrigation.

The San Joaquin Delta area in the northern part of the Valley (San Joaquin and parts of Stanislaus counties) is not suited to cotton or rice production and thus is dominated by alfalfa and sugar beets, with barley and corn being the most important rotational crops. Cotton and rice require good draining land and a hot growing season, whereas the Delta area has poor draining organic soils and occasionally is influenced by cool marine temperatures in summer. Irrigated districts on the west side of San Joaquin and particularly Stanislaus counties have also been the principal producing areas of dry edible beans in California. Acreage in beans has been unimportant relative to other crops in the Valley, however, except in Stanislaus County where it accounted for about 20 per cent of the total field crop acreage. Corn silage

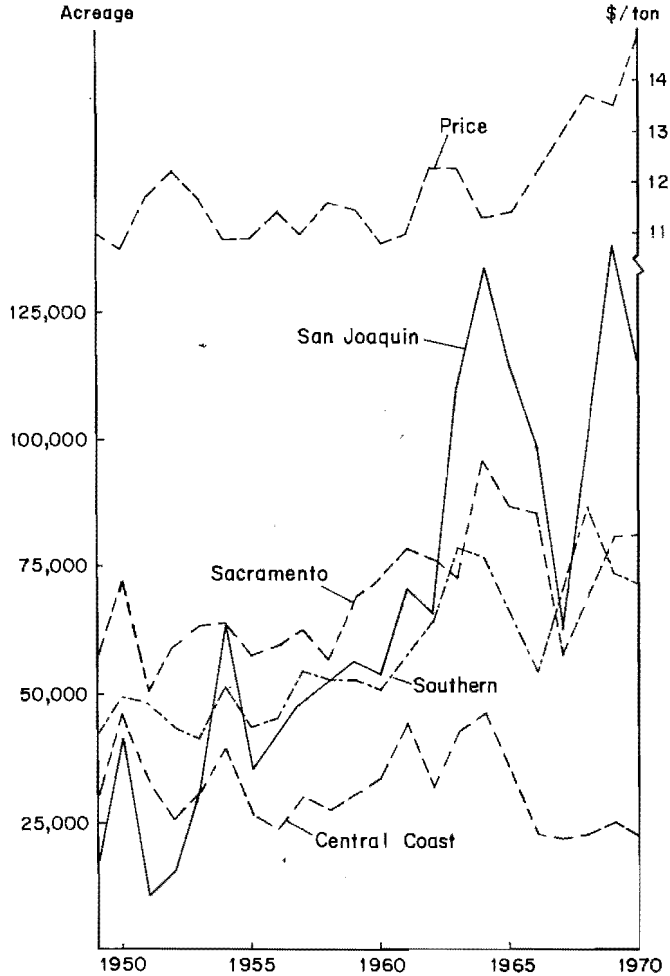

Fig. 7. Sugar Beet acreage and price in California

has generally been of limited significance, but acreage had increased to nearly 100,000 acres by 1970. The San Joaquin Valley has produced approximately 85 per cent of the state's corn silage in recent years.

Sacramento Valley Field crop production in the Sacramento Valley has in many ways been similar to that in the San Joaquin Valley, except that rice and barley have been the dominating crops while cotton has not been grown at all. Cotton does not produce well because the growing season is somewhat shorter than in the San Joaquin Valley. The heavy clay soils in the central part of the Valley are also more conducive to rice production since they require less water for continuous flooding and are firm enough to support heavy harvesting machinery after draining. Rice together with barley, which is a principal crop used in rotation with rice, occupies roughly half of the Sacramento Valley's 1.3 million field crop acres. The Sacramento Valley has also been a principal producer of every other major California field crop, though, with acreages ranging from 50,000 to 150,000 acres each in recent years. Tomatoes, occupy-

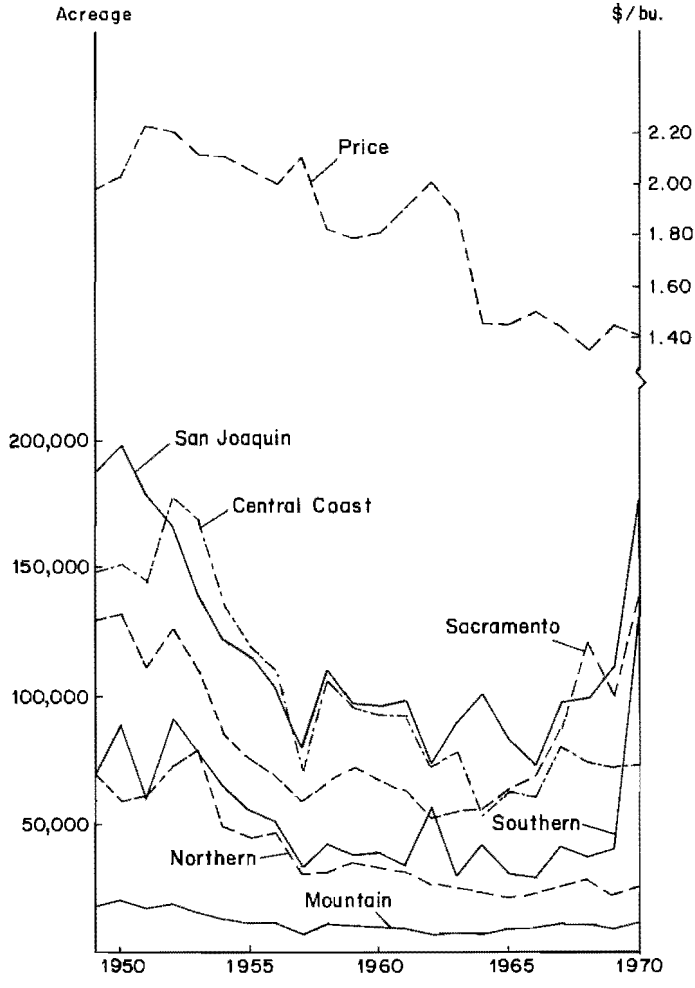

Fig. 8. Wheat acreage and price in California

ing more acreage than any other fruit, nut, or vegetable crop, have never far exceeded 50,000 acres.

Rice, like cotton, has been regulated almost entirely by government programs in recent years as allotments have been imposed since 1955. Although government programs did not play an important role in the rice market prior to and during the Korean War, a severe oversupply problem was created as demand fell at the war's end. Then, with the imposition of allotments on other crops in 1954, acreage continued to increase (fig. 9), and nearly half of the U.S. crop was acquired by the government through CCC loans as prices continued to fall. As a result, growers voted to impose allotments and marketing quotas nationally for 1955 and subsequent years. Acquisitions by the CCC then dropped substantially and have continued to decline since. Although rice acreage has been increasing in recent years in the Sacramento Valley, most of the increase is due to the shifting of allotments from the San Joaquin Valley which has resulted from restrictions on phenoxy-type herbicides. This movement may also continue unless broad-leaf aquatic weed controls com-

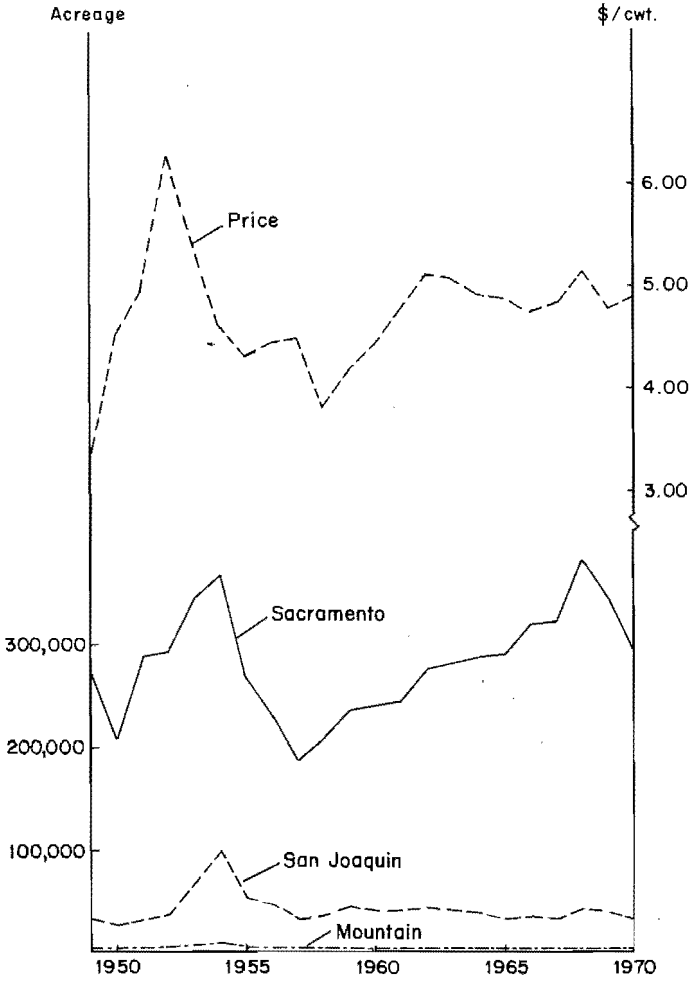

Fig. 9. Rice acreage and price in California

patible with other crops can be found. Comparatively low water cost and available land for expansion are also contributing factors in this shift.

The indirect effect of the rice allotment on other crops is not so easily observable and will not be clear until the statistical investigation is complete. The direct effect of the feed grains and wheat allotments is also not very clear on casual observation, but they appear to have restricted output only slightly (figs. 4, 5, 6, and 8).

Although rice and barley have dominated the rice area in the central part of the Valley (Butte, Colusa, Glenn, and Sutter counties), several other crops have recently achieved some importance due to rotational schemes. Traditionally, rice could be rotated profitably only with winter cereals like barley and wheat. However, both safflower and grain sorghums have been gaining rotational importance with the introduction of new varieties and the discovery that grain sorghum and safflower do well on riceland if phosphates are applied in direct contact with seed. Grain sorghum has been especially profitable in double-crop production in rice-producing areas because the timing of operations for sorghum and rice fits together well. The

development of new varieties which boosted oil content was probably the most important factor leading to the introduction of safflower in California beginning in 1950. The center of production quickly shifted from the San Joaquin Valley to the Sacramento Valley, and a rapid expansion began in 1955 with the imposition of rice allotments. Safflower has been particularly profitable for farms with feed grain bases during the years voluntary feed grain programs have been in effect. Under the voluntary diversion programs, farmers have been able to use diverted acreage in the production of safflower and still receive 50 per cent of diversion payments normally paid them when land is taken completely out of production. Alfalfa has also been of some importance around the perimeter of the rice area, particularly in Yolo and Sacramento counties, with Glenn County recently gaining some importance. Dry edible beans, which had once occupied more than 60,000 acres in Sutter County alone, have been steadily declining in importance as profitability of other crops has improved. Less than 40,000 acres were planted in the entire Valley in 1970.

The Delta area in the southern part of the Valley (Sacramento, Solano, and parts of Yolo counties) has been largely dominated by the production of feed grains, safflower, and wheat while accounting for the major part of the Valley's sugar beet acreage. Since corn and grain sorghum have been influenced by the same sequence of events as in the San Joaquin Valley, relatively the same fluctuations in acreage have resulted (figs. 5, 6). Barley acreage has generally declined throughout the last two decades as a result of hybrid corn and sorghum introduction and the expansion of safflower acreage (fig. 4). The expansion of irrigated acreage and the introduction of Mexican wheat varieties have contributed to the trend away from barley. The trend toward Mexican wheat varieties is more complete in the Sacramento Valley than in other parts of the state as Mexican varieties were introduced there first in the early 1960's. Mexican varieties, which have dominated almost entirely since 1968, are short, semidwarf types, resistant to stripe rust and lodging and capable of higher yields than are the soft white varieties which have traditionally been grown in California. Resistance to lodging permits increased fertilization and irrigation which contributes to the higher yielding capacity. Although not important acreage-wise, almost all the hops produced in the state in the last 15 years have also been grown in Sacramento County. Acreage has declined to little more than 1,000 acres as hops production has been shifting to the Northwest.

Although the dry-land areas, located mainly along the west side of the Valley, once produced large quantities of malt barley, the expansion of irrigation and the shift in emphasis toward feed barley have made dryland farming much less important. The preference of malsters for nonirrigated barley grown on hillsides made the foothill areas particularly well adapted to the production of high-quality malting barley. However, the once sizable California malting barley market has been taken over by midwestern barley which results in differently flavored malt while California feed demand has expanded. The dry-land areas have continued to be dominated by barley and wheat, though, as no more profitable production alternatives exist. Small amounts of oats are also produced with some dry-land safflower occasionally being planted after fallow.

Southern California. Agricultural growing conditions vary greatly in southern California, ranging from the mild southern coastal climate dominated completely by marine influence to the high elevation deserts characterized by extremely wide temperature divergence from night to day and from winter to summer. The most important field crop-producing area by far, though, is the lower elevation desert in Imperial and Coachella valleys with its extremely long growing season. Although southern California could more appropriately be divided into coastal and desert districts for the purposes of this study, the coastal area has been losing rapidly its

importance in the production of field crops due to urbanization. From 1949 to 1970, acreage of all the field crops in the urban counties along the southern coast (Los Angeles, Orange, San Diego, and Ventura counties) steadily declined, with total field crop acreage falling 65 per cent to less than 100,000 acres. Santa Barbara County acreage has also dropped 30 per cent to 55,000 acres and should continue to decline in the future. The desert area, however, has brought an additional 100,000 acres into field crop production during the same period and now has a total acreage well over 600,000. The desert area has produced virtually all of the cotton, grain sorghum, and flaxseed produced in the district while accounting for more than 90 per cent of the sugar beets in recent years. Thus, field crop supply response in southern California largely represents supply response in the Colorado desert. Fruit, nut, or vegetable crops have also not had great impact on southern California field crop response as the most important competitors—oranges, grapes, and lemons—have not exceeded 100,000 acres each in recent years. Furthermore, oranges, grapes, and lemons are all perennial crops and, thus should have little effect on year-to-year acreage variation.

Alfalfa hay is by far the most important field crop produced in the desert area. Imperial County has been the most important county accounting for 150,000 of the district's 250,000 acres. Other important areas have been in Riverside County and the outlying parts of Los Angeles County. Alfalfa production has been particularly advantageous in southern California because of the nearness of the dairy industry concentrated around Los Angeles.

The impact of government programs perhaps has been less significant in southern California than in any other district. The only government program of apparent importance has been the cotton program. Although Imperial Valley cotton has accounted for about 10 per cent of the state's production during the last decade, only 50,000 to 70,000 acres have generally been used. Little cotton had been produced in the Valley since 1930 until the development of effective insect control measures induced southern California cotton acreage to jump from 4,000 to 164,000 acres in the three-year period following the 1950 allotments (fig. 2). Part of this response, however, could be due to growers' efforts to establish acreage history in anticipation of allotments again being imposed. Acreage was cut almost in half when allotments were imposed in 1954 and has since been regulated almost entirely by government programs.

Barley, grain sorghum, and sugar beets have also been of considerable importance in the desert area. When a new sugar beet processing plant was opened near Brawley in 1947, Imperial County became the leading sugar beet-producing county in the state. Sufficient acreage history had been compiled by the time proportionate shares were imposed, though, so that no marked cutbacks were evident (fig. 7).[49] Barley and sorghum have been used principally as rotational crops with the high-return crops (sugar beets, alfalfa, and cotton) just as in the central part of the San Joaquin Valley. Although flaxseed was once important, acreage began to decline exponentially when price dropped almost 50 per cent in 1949 until only about 2,000 acres were left in production through the late 1960's.

Although wheat along with oats and barley had typically been produced in somewhat insignificant amounts in the highland areas (mostly in parts of Los Angeles and Riverside counties), the center of production quickly shifted to the Imperial Valley with the introduction of Mexican wheat varieties in 1969. Mexican varieties

[49] Although acreage fell to a low in 1966, that low cannot be attributed to the 1966 acreage controls since the state's acreage quota was not near filled in that year. Because sugar beet proportionate shares are reallocated each year by the Agricultural Stabilization and Conservation Service until the state's quota is filled, no grower is really constrained except through normal contracts with processors unless the state quota is reached.

have had their most dramatic effect in southern California, specifically in Imperial County, as the district's production more than tripled by 1970. Acreage in Imperial County jumped from less than 4,000 in 1968 to about 70,000 acres by 1970. The shift has not continued, however, as yields did not quite meet expectations. Furthermore, a new higher yielding barley variety which caused a partial reversal was released by the University of California in 1971.

Dry edible beans, grown only in the cool coastal area, have been gradually declining in importance throughout the last two decades and because of urbanization. will likely continue to fall. Acreage had fallen from 125,000 acres in 1949 to less than 20,000 acres in 1970.

Central Coast. The Central Coast is the only district where fruit, nut, and vegetable crop acreage is comparable with that of field crops. Six such crops have exceeded 20,000 acres in recent years. However, five of these crops are perennial crops, while most of the acreage of the sixth, lettuce, has been concentrated in Monterey County. The greatest concentration of field crop acreage has been in San Luis Obispo County with Monterey County of secondary importance.

Much of the district is mountainous and forested with other parts being heavily populated; thus, many of the counties have only insignificant acreages capable of field crop production. As a result, the district has been of little significance in the state's production of all crops except for wheat, grain hay, and perhaps dry edible beans. San Luis Obispo County has been almost entirely dominated by wheat, barley, and grain hay production. The impact of the wheat program has probably been greater than in any other area of the state because of wheat's importance. This county alone accounts for nearly one-fifth of the state's total acreage, although yields are less than half of the state average. Total acreage of the three crops has remained nearly constant at 190,000 acres throughout the last 20 years.

Monterey County has been of equal importance in the production of barley but of less importance in wheat and grain hay production. Other important crops competing with lettuce and other vegetables have been dry edible beans and sugar beets. Sugar beet acreage has varied from 15,000 to 30,000 acres while bean acreage has ranged from 20,000 to 40,000 acres in recent years. Alameda, Contra Costa, San Benito, and Santa Clara counties have also had small acreages of barley and grain hay, but all other production has been of very little significance.

Northern and mountain Regions. The northern and mountain areas of the state, being extremely mountainous or wooded, have very little acreage suitable for field crop production. Due to the extremely cold winters and short growing seasons, only a very few crops are capable of profitable production. Barley, wheat, and alfalfa have been the dominating crops with small amounts of grain hay and oats also being grown.

The most important producing areas have been in Siskiyou, Modoc, Lassen, and Placer counties.[50] Total acreage in the Tulelake area (in Siskiyou and Modoc counties) has been relatively stable with barley being the most important crop. Wheat acreage in the Tulelake basin, which accounts for most of the Durum wheat production in the state, has been declining in recent years as alfalfa production has increased. Total acreage in Siskiyou and Modoc counties, which also includes a few other small producing areas, has been nearly constant at 180,000 acres. In the other small areas of production in the northeastern interior, particularly in Lassen County, alfalfa has largely dominated, with wheat and grain hay being of secondary importance. However, only about 30,000 acres have been in field crops in Lassen County with other areas being of much less importance.

[50] Actually, Placer County should more properly be included in the Sacramento Valley since most of the production takes place in the south-western corner of the county which protrudes into the valley.

Choice of Decision and Information Variables for Econometric Analysis

It is apparent from the foregoing discussion that numerous forces are operative in the supply response of many of the field crops even at a district level. Decision variables of apparent importance in explaining supply response are acreage, fertilization, irrigation, machinery use, labor, etc. Information variables of importance in the decision-making process would be the farm prices of the various commodities produced, input prices, and yields associated with the various technologies currently available. Unfortunately, few data are available for all decision variables except acreage. Furthermore, the sparse data that are available for those variables indicate that they are probably influenced almost entirely by currently available technology rather than prices and other variables of general theoretical importance. The problem in the analysis of decisions other than acreage, then, is the dynamic characterization of the set of possible decisions D. As new technologies become available, the set D expands; and, apparently, prices and other variables during the period have been such that adoption has been beneficial. Thus, it appears that decisions other than acreage are explained almost solely by the dynamic expansion of the set D. (The study of these decision variables and the resulting yields is set out in Appendix A.)

A dynamic characterization of the set of possible decisions with respect to acreage, however, is not so difficult. Total field crop acreage has been nearly constant during the last two decades at about 6.5 million acres. Although crop rotation requirements might also seem important, rotational schemes have been of declining significance as irrigation water and nitrogen fertilization constraints have been relaxed. Thirty years ago land had to be retired or relieved periodically to allow water and nitrogen levels to be restored. However, with the establishment of a new Shell Oil refinery, sulphuric acid—which previously had been dumped in the Sacramento River—began to be neutralized with excess ammonia, another by-product of the refinement process, producing ammonium sulphate at reasonable prices. Thus, with the development of the California Water Plan in addition to the new oil refinement methods, both water and nitrogenous fertilizer became available for agricultural use in increased quantities. Hence, rotational considerations no longer hold the importance they once did, and economic considerations are now of increased significance.[51] The major consideration of continuing importance seems to be that sugar beets cannot be followed by a second crop of sugar beets for reasons of biological control. However, the influence of sugar beet processors in filling processing plant capacity has prevented any erratic fluctuation in acreage. Thus, rotational aspects will not be considered as important in this analysis of acreage response, and any influence they might have on the set of possible decisions will be disregarded.[52] Even though some rotational considerations might persist, it appears that all crops become competitive at the margin; thus, the complementarities that might be associated with rigid rotational requirements are not expected.

The only other important problem with respect to the dynamic variation of the decision set seems to be presented by alfalfa. Since alfalfa is a perennial crop, acreage decisions for alfalfa carry an impact for more than one production period. Alfalfa could still be handled in the Markovian framework presented in the first part of this study, however, since prior subjective distributions can be formed for several periods in the future based on the current subjective distributions and the knowledge of the Markovian processes available to the decision-maker. The correct approach would

[51] Although the development of irrigation facilities and new sources of fertilizer might be of importance in defining the decision set, a lack of data has prevented the inclusion of such variables in the statistical analysis.

[52] The discussion of rotational importance here is based on a private conversation with Dr. Albert Ulrich, Department of Soils and Plant Nutrition, University of California, Berkeley.

then be to describe the decision set by the age distribution of the existing alfalfa acreage. The decision to terminate alfalfa production on any piece of land would depend on the age of the acreage and expectations associated with the production of all crops that could possibly be produced on the land. A decision to plant alfalfa would depend on the expectations associated with the production of alfalfa and its alternatives for as long in the future as one planting can continue to produce. Since age-distribution data were unavailable, the approach actually used in the empirical analysis corresponds to the more traditional partial adjustment model. The acreage in any period is posited to depend on a proportion of the previous year's acreage and the new plantings determined by current subjective beliefs.

The information variables which have been used in the econometric analysis of acreage response are yields and prices (at the farm level) of field crops. The acreage of other crops in California has been comparatively small (except for a few perennial fruit crops) as field crops are generally farmed on a more extensive basis. In 1970 the acreage of field crops in California was approximately eight times that of vegetables and five times that of all fruits and nuts (California Crop and Livestock Reporting Service, 1970, 1971*a*, 1971*b*). Also, due to the perennial nature of fruit and nut crops, an even greater amount of the annual acreage variation in California is accounted for by field crops. Therefore, prices and yields of other crops have not been included. Although prices of inputs are also relevant information variables, much the same inputs are used in the production of all field crops. Thus, input prices are apparently not major forces affecting the allocation of land to the production of one or another field crop.

Another set of variables excluded from the analysis in most cases refers to the introduction of new technology. Apparently, the development of new varieties of several crops has played an important role in determining acreage response. Depending on the dissemination of new varietal information, a varying amount of acreage will be planted to some new variety when it is first introduced. Unfortunately, variables of this kind are extremely difficult to quantify and much more difficult to predict. Even with the exclusion of varietal information variables, however, the model should capture the explanation of changing acreage response once adoption has begun since higher yields predicted for the new varieties will be realized and reflected in the other information variables used in the investigation. This approach has appeared to suffice for all crops considered except wheat which has been affected by the introduction of Mexican wheat varieties in the late 1960's.

Finally, one further simplification was made in the selection of information variables. Given the large number of competing crops and the scarcity of data, it appeared desirable to aggregate the price and yield variables for each of the crops. Assuming the decision-maker is concerned only with the monetary aspects of outcomes, the information variables ultimately used were returns—that is, price times yield—for each of the California field crops.[53] Hence, for the application of the econometric model to the field crop sector, d_t was taken as a vector of acreages and s_t as a vector of returns per acre of the respective field crops. Acreage planted and acreage harvested were treated as identical since distinguishing data are not available for all of the crops.

[53]The reader might possibly think the subjective model developed in the first part of this study is somewhat naive when the information variables employed are returns per acre; that is, one might suppose that the level of returns per acre for field crops has been steadily rising through time due to inflation and technological progress so that decision-makers would expect an upward trend in returns in addition to any secular deviation. Subjective parameters in such a case would also include a subjective time trend. However, a preliminary analysis of the fourty time series of returns for the important California field crops included in the econometric analysis indicated that only thirteen of the series demonstrated significant positive trends while ten of the series showed negative trends. Returns per acre for field crops in many cases have been near constant while yields have been increasing due to the downward trend in prices.

Estimation of Acreage Response

Based on the above discussion, the general form of the acreage response equations that have been estimated is[54]

$$
\begin{aligned}
d_{tj} = {} & A_{oj} + \tilde{A}_{1j}(1-\theta_j)^{t-t_o} + A_{1jj}\theta_j \sum_{k=0}^{t-t_o-1} (1-\theta_j)^k s_{t-k-1,j} \qquad (4.1)\\
& + \sum_{i\in C(j)} A_{1ji}\theta_j \sum_{k=0}^{t-t_o-1} (1-\theta_j)^k s_{t-k-1,i} + \tilde{A}_{2j}\phi_j^{t-t_o} \\
& + A_{2jj}^{j}(1-\phi_j) \sum_{k=0}^{t-t_o-1} \phi_j^k \Bigg[s_{t-k-1,j} - (1-\theta_j)^{t-t_o-k-1} m_{t_o j} \\
& - \theta_j \sum_{h=0}^{t-t_o-k-2} (1-\theta_j)^h s_{t-k-h-2,j} \Bigg]^2 \\
& + (1-\phi_j) \sum_{i\in C(j)} A_{2ii}^{j} \sum_{k=0}^{t-t_o-1} \phi_j^k \Bigg[s_{t-k-1,i} - (1-\theta_j)^{t-t_o-k-1} m_{t_o i} \\
& - \theta_j \sum_{h=0}^{t-t_o-k-2} (1-\theta_j)^h s_{t-k-h-2,i} \Bigg]^2 \\
& + (1-\phi_j) \sum_{i\in C(j)} A_{2ji}^{j} \sum_{k=0}^{t-t_o-1} \phi_j^k \Bigg[s_{t-k-1,j} - (1-\theta_j)^{t-t_o-k-1} m_{t_o j} \\
& - \theta_j \sum_{h=0}^{t-t_o-k-2} (1-\theta_j)^h s_{t-k-h-2,j} \Bigg] \Bigg[s_{t-k-1,i} - (1-\theta_j)^{t-t_o-k-1} m_{t_o i} \\
& - \theta_j \sum_{h=0}^{t-t_o-k-2} (1-\theta_j)^h s'_{t-k-h-2,i} \Bigg] \\
& + (1-\phi_j) \sum_{i\in C(j)} \sum_{\substack{v\in C(j)\\ v\neq j,i}} A_{2iv}^{j} \sum_{k=0}^{t-t_o-1} \phi_j^k \Bigg[s_{t-k-1,i} - (1-\theta_j)^{t-t_o-k-1} m_{t_o i} \\
& - \theta_j \sum_{h=0}^{t-t_o-k-2} (1-\theta_j)^h s_{t-k-h-2,i} \Bigg] \Bigg[s_{t-k-1,v} - (1-\theta_j)^{t-t_o-k-1} m_{t_o v} \\
& - \theta_j \sum_{h=0}^{t-t_o-k-2} (1-\theta_j)^h s_{t-k-h-2,v} \Bigg] \\
& + A_{3jj} I_{tj}^{*} + \sum_{k\in C(j)} A_{3jk} I_{tk}^{*} + A_{4jj} d_{tj}^{**} + \sum_{k\in C(j)} A_{4jk} d_{tk}^{**} \\
& + A_{5jj} p_{tj}^{*} + \sum_{k\in C(j)} A_{5jk} p_{tk}^{*} + A_{6j} d_{tj}^{+} + \varepsilon_{tj}
\end{aligned}
$$

where

$$C(j) = \{i \mid \text{crops } i \text{ and } j \text{ are major competitors for land}\}$$

[54]The usual practice of defining the exact form of each regression equation prior to the reporting of empirical results has been dispensed with in this study due to the large number of equations. The general form of the equations is given here; specific variable descriptions are then given in the tables reporting regression results.

and

$$A_2 = \begin{bmatrix} A^1_{211} \cdots A^1_{21n} A^1_{222} \cdots A^1_{22n} A^1_{233} \cdots A^1_{2,n-2,n} A^1_{2,n-1,n-1} A^1_{2,n-1,n} A^1_{2nn} \\ A^2_{211} \cdots A^2_{21n} A^2_{222} \cdots A^2_{22n} A^2_{233} \cdots A^2_{2,n-2,n} A^2_{2,n-1,n-1} A^2_{2,n-1,n} A^2_{2nn} \\ \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \\ A^p_{211} \cdots A^p_{21n} A^p_{222} \cdots A^p_{22n} A^p_{233} \cdots A^p_{2,n-2,n} A^p_{2,n-1,n-1} A^p_{2,n-1,n} A^p_{2nn} \end{bmatrix}$$

In each case $(1 - \theta_j)\phi^k_j$ has now been changed to $(1 - \phi_j)\phi^k_j$ so that A^j_{2ik} can be more simply interpreted as the coefficient of subjective variance or covariance as the case may be.

As can be easily verified, all the terms in (4.1) have a quite simple interpretation. The first term A_{oj} is the usual intercept term employed in regression analysis. The second term represents the effects of all subjective-mean-of-returns knowledge (or price times yield expectations) held in the base period t_o. These effects, of course, decrease geometrically with time representing the discounting of information from far in the past. The third term represents the effect of subjective-mean knowledge accumulated since t_o for the crop of interest. Observations are weighted geometrically since their contribution toward the subjective mean decreases at a constant rate with increasing time lags. The fourth term represents the corresponding effects of subjective-mean knowledge accumulated since t_o for all competing crops. The fifth term corresponds to the second term but represents the effects of all subjective-risk (variance and covariance) knowledge held at t_o. Like subjective-mean knowledge at t_o, the fifth term decreases geometrically with time although not necessarily at the same rate.

The sixth, seventh, eighth, and ninth terms represent the entrance of subjective-risk knowledge accumulated since t_o. The sixth term represents the effect of the subjective-variance-of-returns knowledge accumulated since t_o for the crop of interest, while the seventh term represents the effects of the corresponding knowledge for competing crops. Similarly, the eigth term represents the effects of subjective-covariance knowledge accumulated since t_o between the crop of interest and all competing crops, while the ninth term considers the subjective covariance between all pairs of competing crops. In each case one finds second-order terms geometrically weighting either squares or cross products of past observed deviations of observations about corresponding subjective prior expectations. In each case the prior subjective mean is formed by appropriately discounting subjective knowledge held in t_o and adding the subjective-mean knowledge which has been accumulated since t_o (the same expressions which appear in the third and fourth terms). Although the subjective-mean knowledge held in t_o (given by m_{t_o}), used in forming the subjective risk terms, could be estimated by the iterative technique discussed in section 4, in this study it is estimated on the basis of historical data for each combination of θ and ϕ considered in the maximum likelihood search. Hence, as indicated in section 4, all the remaining unknown coefficients in the model can be estimated by ordinary regression for given combinations of θ and ϕ, as indicated by (4.2) below.

Of course, the remaining (tenth through sixteenth) terms in the model correspond to the effects of the government program variables discussed in section 3. The even-numbered terms represent the direct effects of the program variables for the crop of interest, while the odd-numbered terms correspond to the effects of the programs directed at competing crops. As indicated in section 3, the diversion variables for competing crops affect the crop of interest only through the allotment variables for competing crops; thus, no diversion term for competing crops corresponding to the sixteenth term appears.

For each acreage equation in each district, the set of competing crops, $C(j)$, has been determined on the basis of the geographical, irrigational, and rotational aspects of production. The sets of competing crops, as well as the set of included variables, were then occasionally modified when results contrary to implications of economic theory were indicated.

Of course, many of the coefficients in (4.1) drop out of the estimation problem since some crops have no corresponding government programs, and other programs do not carry as many provisions as are provided for in the model. Also, some allotments have been nearly constant allowing the government program component of the model to be simplified as in (2.21) and (2.23). Nevertheless, the available data were not sufficient to estimate (4.1) completely. Therefore, the ninth term of (4.1) containing cross-products among all pairs of competing crops is omitted since some studies (Carter and Dean, 1960) suggested that only the subjective covariances in the eighth term may be of importance in the decision-making process.

Special problems were also presented by the voluntary feed grains program. Although the programs have been in effect since 1961, only corn and grain sorghum have been included in some years. Barley did not come into the program in 1961, 1967, and 1968.[55] Unfortunately, neither allotment participation nor diversion activities for the feed-grain programs are attributed to the various crops in government program data. To retain continuity in the model, however, it appeared desirable at least to allocate participation and diversion between barley and the other crops in the program. Therefore, estimated barley participation and diversion and estimated corn-sorghum participation and diversion variables were constructed by linearly interpolating the differences in feed-grain participation and diversion, respectively, between years when barley entered and exited the programs.

Acreage equations similar to (4.1) (omitting the ninth term) have then been estimated for each of the eight important California field crops in each of the six districts indicated in figure 1.[56] Crops selected for investigation were barley, cotton, rice, sugar beets, wheat, alfalfa hay, corn, and grain sorghum. Other California field crops (dry edible beans, safflower, oats, silage, hops, and hay other than alfalfa) were not included in the analysis since they are relatively unimportant, and in most cases reliable data were not available. It should be noted, however, that reliable data were not always available even for the important crops included. (The methods used for adjusting data obtained from perhaps unreliable sources are discussed in Appendix C.) In a few cases the adjusted series appeared still to contain an occasional outlying observation. When the source of the outlying datum was traced to an inplausible observation from an unreliable source, the data for that year were essentially discounted by including a binary variable for that year. It also became necessary to appeal to shift variables because of the tremendous shift toward Mexican wheat varieties in 1970 and the effect of improved insect controls developed for cotton in the early 1950's in the Imperial Valley as no variables were included in the model for the dissemination of new varietal information or the development of cultural practices.

The period of time over which the econometric model was estimated is 1949 to 1970. Thus, $t_o = 1949$, $t_f = 1970$, and $T = 22$. The selection of the period was based on the following considerations:

1. Much of the 1940's were apparently highly influenced by World War II and early postwar complications.

[55] Barley was also excluded in 1971, but only data through 1970 were available at the time of estimation.

[56] Of course, some of the crops are not grown in all districts so some districts will have fewer than eight acreage equations.

2. To include restricting government program activities prior to 1950, the estimation period would have to be extended back as early as the 1930's.
3. Total crop acreage in California was near its peak by 1949 while total acreage prior to the late 1940's was increasing significantly.
4. Mechanization of field crop operations was essentially complete by 1949.
5. Many of the publications from which data were obtained were only available beyond the late 1940's; data beyond 1970 were not yet available at the time of estimation.

Due to the large number of acreage equations to be estimated, the most computationally appealing method, indicated in (3.26) through (3.29), was selected as the general estimation procedure. At each point (θ_i, ϕ_i), for which the likelihood function was evaluated, m_{t_o} was estimated by $\hat{m}_{t_o}(\theta_i)$ on the basis of statewide data prior to t_o adjusted to district levels by observed variation among districts beyond t_o. Although simultaneous estimation methods characterized by asymptotic efficiency were discussed, only simple single equation methods were used in estimation because (1) other decision variables have already been excluded thus destroying asymptotic efficiency and (2) when θ and ϕ are allowed to vary over equations, the maximum likelihood search becomes much more computationally complicated if simultaneous methods are used. For each (θ_i, ϕ_i) chosen, the regression equations actually estimated via a standard regression program were then of the following linear form:

$$\begin{aligned} d_{tj} = {} & A_{oj} + \tilde{A}_{1j}\tilde{Z}_{1t} + A_{1jj}Z_{1tj} + \sum_{i \in C(j)} A_{1ji}Z_{1ti} \\ & + \tilde{A}_{2j}\tilde{Z}_{2j} + A^j_{2jj}Z_{2tjj} + \sum_{i \in C(j)} A^j_{2ii}Z_{2tii} \\ & + \sum_{i \in C(j)} A^j_{2ji}Z_{2tji} + A_{3jj}Z_{3tj} + \sum_{k \in C(j)} A_{3jk}Z_{3tk} \\ & + A_{4jj}Z_{4tj} + \sum_{k \in C(j)} A_{4jk}Z_{4tk} + A_{5jj}Z_{5tj} \\ & + \sum_{k \in C(j)} A_{5jk}Z_{5tk} + A_{6j}Z_{6tj} + \sum_{\tau \in D(j)} A_{7\tau j}Z_{7t\tau} + \varepsilon_{tj} \end{aligned} \tag{4.2}$$

where

$$\tilde{Z}_{1t} = (1 - \theta_j)^{t - t_o}$$

$$Z_{1ti} = \theta_j \sum_{k=0}^{t-t_o-1} (1 - \theta_j)^k s_{t-k-1,i} \qquad i = 1, \ldots, n$$

$$\tilde{Z}_{2t} = \phi_j^{t-t_o}$$

$$\begin{aligned} Z_{2tij} = (1 - \phi_j) \sum_{k=0}^{t-t_o-1} \phi_j^k \Bigg[& s_{t-k-1,i} - (1 - \theta_j)^{t-t_o-k-1} m_{t_o i} \\ & - \theta_j \sum_{k=0}^{t-t_o-k-2} (1 - \theta_j)^h s_{t-k-h-2,i} \Bigg] \Bigg[s_{t-k-1,j} \\ & - (1 - \theta_j)^{t-t_o-k-1} m_{t_o j} - \theta_j \sum_{h=0}^{t-t_o-k-2} (1 - \theta_j)^h s_{t-k-h-2,j} \Bigg] \\ & \qquad i = 1, \ldots, n \qquad j = 1, \ldots, n \end{aligned}$$

$$Z_{3tk} = I^*_{tk} \qquad k = 1, \ldots, q$$
$$Z_{4tk} = d^{**}_{tk} \qquad k = 1, \ldots, q$$
$$Z_{5tk} = p^*_{tk} \qquad k = 1, \ldots, q$$
$$Z_{6tj} = d^+_{tj}$$
$$Z_{7t\tau} = \begin{cases} 1 & \text{if } t = \tau, \\ 0 & \text{if } t \neq \tau, \end{cases}$$

$D(j)$ = $\{\tau | \text{shift variables are included for year } \tau\}$

$s_{t,j}$ = total returns per acre, i.e., prices times yield of crop j[57]

I^*_{tj} = allotment indicator for crop j times the rate of participation when voluntary

d^{**}_{tj} = allotment for crop j times rate of participation when voluntary

p^*_{tj} = preannounced price-support level for crop j times rate of participation when the program is voluntary

d^+_{tj} = acres diverted under the program for crop j.

For purposes of reporting results, coefficients are labeled as follows:[58]

A_{oj} = constant

$\tilde{A}_{1j}$ = subjective mean (of returns weighted by A_{1j}.) in t_o

A_{1ji} = (coefficient of the) subjective (mean of) returns for crop i

$\tilde{A}_{2j}$ = subjective risk (associated with returns weighted by A^j_{2ik}, $i, k = 1, \ldots, n$) in t_o

A^j_{2ii} = (coefficient of) subjective risk (or variance of) returns of crop i

A^j_{2ji} = (coefficient of) subjective covariance (of returns between crop j and) crop i

A_{3ji} = (coefficient of the) crop i allotment indicator (variable times the proportion of compliance when voluntary)

A_{4ji} = (coefficient of the) crop i allotment (times the proportion of compliance when voluntary)

A_{5ji} = (coefficient of the) crop i (price) support (times the proportion of) eligibility (when compliance is voluntary)

A_{6jj} = (coefficient of) diversion or estimated diversion for crop j

$A_{7\tau j}$ = (coefficient of) dummy variable for year τ.

Although an attempt was made to estimate the government program component of the model in its most general form corresponding to (2.27), simplifications were often made on the basis of the assumptions in (2.21) and (2.23) when plausible. Hence, the estimated equations for any given crop and district may correspond to any one of the four models in (2.24) through (2.27). The reader is then cautioned to interpret the coefficient estimates accordingly where such simplifications have been made.

Three major hypotheses pertaining to risk were also of special interest in the empirical investigation:

[57] In the case of sugar beets, the $s_{t,j}$ variables were augmented by the average government payment per unit of output made to growers. Since the payment is made in the form of a subsidy and the size of the payment is not known prior to decision-making, $s^{**}_{t,j}$ is nonzero, thus indicating such a procedure.

[58] Words in parentheses are not included in the labels given in the tabulation of results.

a. Decisions are not significantly affected by subjective variances or covariances.
b. Decisions are not significantly affected by the subjective covariances.
c. The temporal lag distributions for the subjective mean and variance are equal, i.e., $\theta = 1 - \phi$.

Accordingly, four variants of the model given in (4.2) were used in the acreage response investigation. Under Model 1 corresponding to (a) above, $\tilde{A}_{2j}$, A^j_{2ii}, and A^j_{2ji} were constrained to be zero for $i = 1, \ldots, n$. Hence, ϕ drops out of Model 1 and only a one-dimensional likelihood search on θ is required. Model 1 is then essentially just a standard multivariate geometric lag model corresponding to (1.15). Under Model 2 corresponding to (b) above, the only constraint is $A^j_{2ji} = 0$ for all $i \neq j$. Hence, the two-dimensional likelihood search method in (3.26) through (3.29) is used directly. Under Model 3 corresponding to (c) above, the constraint $\theta = 1 - \phi$ was imposed. Although this model was investigated both with and without covariances, results are only reported for the case when covariances do not enter. Thus, under Model 3, constraints are $\theta = 1 - \phi$ and $A^j_{2ji} = 0$ for all $i \neq j$. Additionally, however, since multicollinearity results when $(1 - \theta)^{t-t_0} = \phi^{t-t_0}$, $\tilde{A}_{2j}$ is also excluded from Model 3. Hence, the estimated $\tilde{A}_{1j}$ will actually be an estimate of $\tilde{A}_{1j} + \tilde{A}_{2j}$ under the hypothesis of Model 3. Again, only a one-dimensional likelihood search is required. Finally, under Model 4 the model in (4.2) was estimated without constraints.

The search procedures employed were as follows: For the models requiring only a one-dimensional search on the unit interval, the conditionally maximized likelihood function was evaluated by means of a standard regression program for $\theta = 0.1, 0.2, \ldots, 0.9$. In all cases the likelihood function appeared to behave smoothly although an occasional likelihood function with two local maxima was found. In every case the nine-point plots appeared to indicate concavity in the neighborhood of the local maxima. Hence, a Fibonacci search was invoked from each of the indicated local maxima.[59] In each case a sufficient number of points were evaluated so as to locate the maximum likelihood estimate of θ with an accuracy of 0.006 under the assumption of local concavity. The globally maximizing θ was then chosen as the maximum likelihood estimate. Although in a few cases the likelihood function appeared to continue to increase as θ approached zero or one, an evaluation of the likelihood function in the limit indicated the maximum likelihood estimates were in the interior of the unit interval. One-dimensional likelihood functions (maximized at each point with respect to all the other coefficients) typical of those found by Model 1 are given in figures 10, 12, 14, 16, and 18. An ordinal representation of the likelihood functions found by Model 3 is evident in figures 11, 13, 15, 17, and 19.

For the models requiring a two-dimensional search in the unit square, the conditionally maximized likelihood function was evaluated for all combinations of $\theta = 0.1, 0.3, \ldots, 0.9$ and $\phi = 0.1, 0.3, \ldots, 0.9$. Again, the likelihood function appeared to behave smoothly, but two local maxima were indicated in many cases due to multicollinearity presented by the two variables $(1 - \theta)^{t-t_0}$ and ϕ^{t-t_0}. According to the regression rountine employed, one of the above variables was dropped from the calculations as the two variables approached collinearity along the line $\theta = 1 - \phi$ to maintain nonsingularity in the estimation of other coefficients. Hence, a trough often resulted along the line $\theta = 1 - \phi$ as the *explanation* associated with the additional variable was lost. In cases where the global maximum fell close to the

[59]The well-known Fibonacci search method is the optimal one-dimensional search method in the sense that it minimizes the maximum possible interval of uncertainty in which the maximum of a unimodal function can lie after a fixed number of points on the function have been evaluated. For a detailed discussion of the method, see Aoki (1967) or Howard (1960).

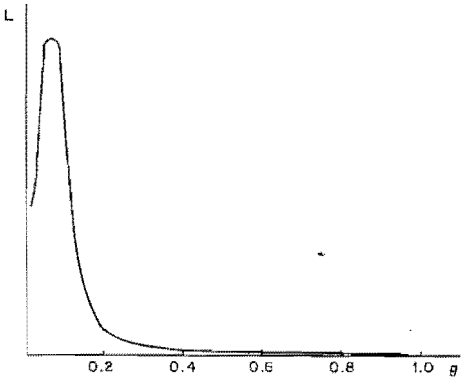

Fig. 10. Likelihood function found by Model 1 for grain sorghum in the San Joaquin Valley

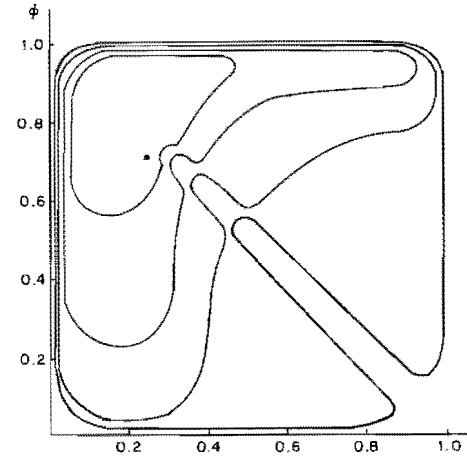

Fig. 11. Likelihood contours found by Model 2 for grain sorghum in the San Joaquin Valley

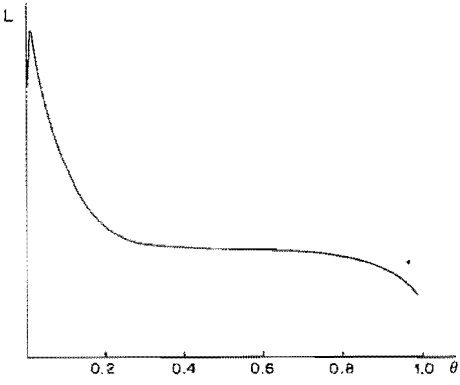

Fig. 12. Likelihood function found by Model 1 for wheat in the Sacramento Valley

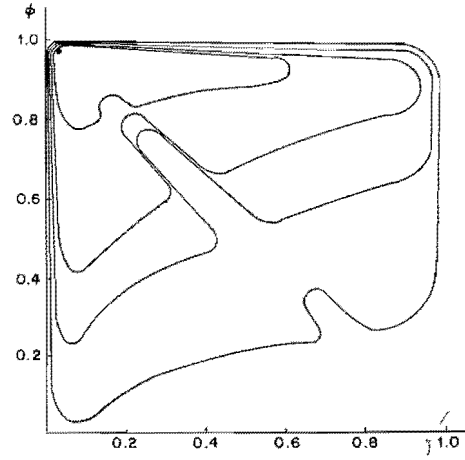

Fig. 13. Likelihood contours found by Model 2 for wheat in the Sacramento Valley

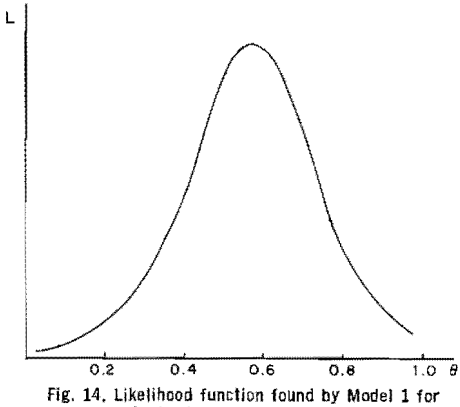

Fig. 14. Likelihood function found by Model 1 for barley in southern California

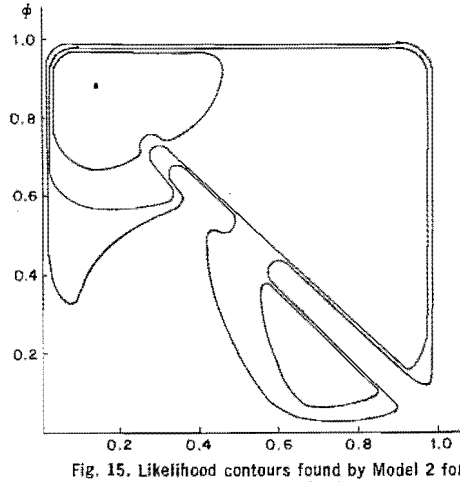

Fig. 15. Likelihood contours found by Model 2 for barley in southern California

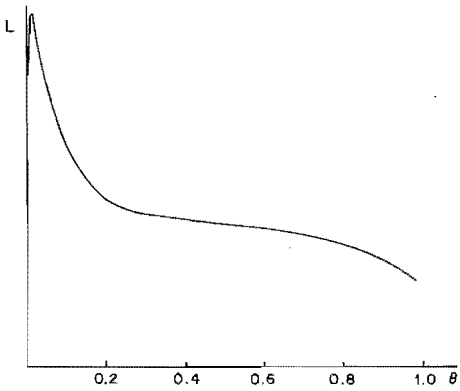

Fig. 16. Likelihood function found by Model 1 for sugar beets in the Central Coast

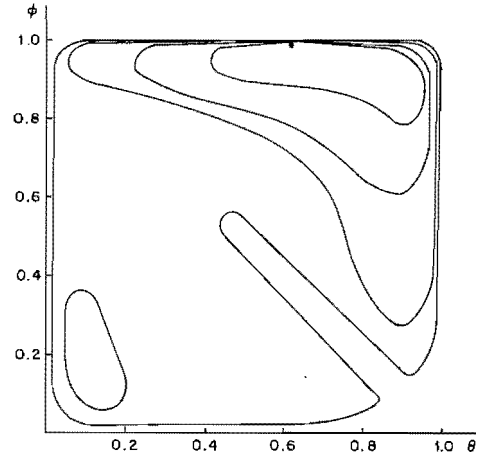

Fig. 17. Likelihood contours found by Model 2 for sugar beets in the Central Coast

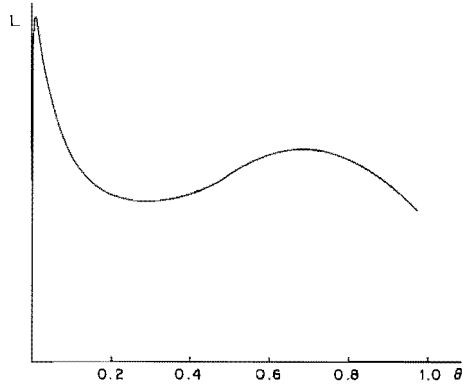

Fig. 18. Likelihood function found by Model 1 for alfalfa hay in northern California

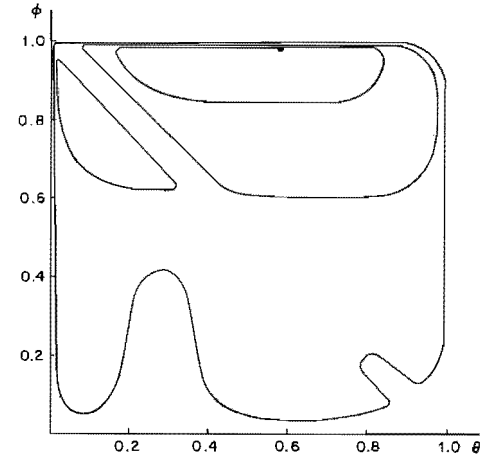

Fig. 19. Likelihood contours found by Model 2 for alfalfa hay in northern California

trough, a local maximum was usually found on the opposite side. In each case an additional pattern search was carried through from each of the local maxima indicated by the coarse-grid search. Although details of the method will not be discussed here, the method was essentially a steepest ascent procedure with some modifications designed to take advantage of the diagonal ridges found on each side of the trough. Barring unusual circumstances, the method was constructed so as to locate the maximum likelihood estimates of θ and ϕ to an accuracy of 0.01. Again, the globally maximizing θ and ϕ were chosen as the maximum likelihood estimates. Likelihood contours typical of those found by Model 2 are given in figures 11, 13, 15, 17, and 19.[60] A plot of the likelihood maximizing values of θ and ϕ for the reported equations estimated by Model 2 is given in figure 20, in which the concentration of points just off the diagonal ($\theta = 1 - \phi$) caused by the trough is apparent. However, a tendency toward the diagonal is also evident as all but five or six of the points appear as though held away from the diagonal only by multicollinearity as $\theta \to 1 - \phi$. Fur-

[60] Of course, the contours are only approximate as not a great number of points on the likelihood functions have actually been evaluated.

thermore, three of the outlying points account for much smaller acreages than any of the remaining points. After their removal, at least 14 of the remaining 17 points appear close to the diagonal. Thus, results tend to favor hypothesis (c).

Although results for Models 1, 2, and 3 are reported in Tables 2 through 7, results for Model 4 are not reported since covariance expectations appeared to play no significant role for any of the crops. Hypothesis (b) was thus accepted.

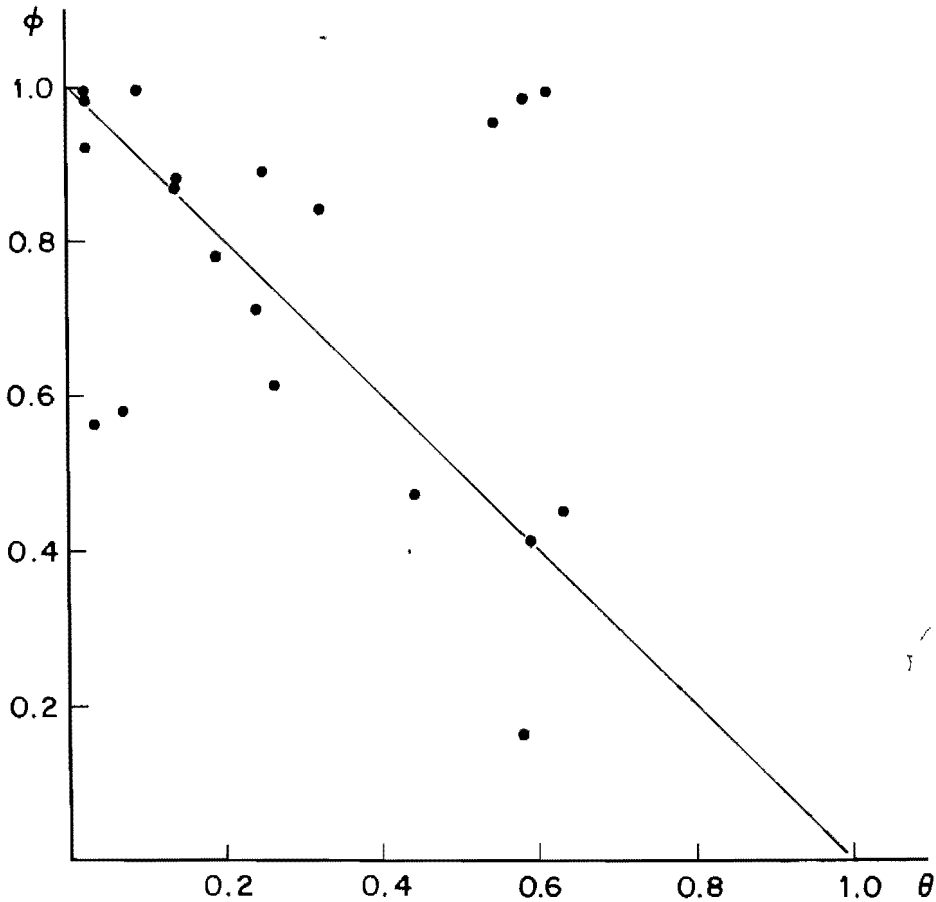

Fig. 20. Likelihood Maximizing Points Found for Reported Equations Estimated by Model 2

TABLE 2
ESTIMATED ACREAGE RELATIONSHIPS FOR THE SAN JOAQUIN VALLEY

Barley—Given the maximum likelihood estimate of theta = 0.006*

(1) Constant	Cotton returns subjective mean	Cotton allotment indicator	Alfalfa returns subjective mean	Barley returns subjective mean	Barley program estimated participation	Subjective mean in 1949	R-SQR D-W
28450241.	−40890.388	186255.45	−249418.29	332497.25	−155321.46	−27891067.	0.8770
10364068.	16130.718	37027.33	125695.41	201528.85	60354.62	10372955.	1.7548

Barley—Given the maximum likelihood estimates of theta = 0.030 and phi = 0.560

(2) Constant	Cotton returns subjective mean	Cotton allotment indicator	Alfalfa returns subjective mean	Barley returns subjective mean	Barley program estimated participation	Subjective mean in 1949	Subjective risk in 1949	Alfalfa returns subjective risk	R-SQR D-W
17171005.	−20013.647	172754.59	−112758.73	89194.429	−152223.96	−16944313.	394933.85	128.42507	0.9661
2184455.	2874.640	22623.23	17429.87	23006.844	34770.83	2235749.	70459.13	23.40094	2.7172

Barley—Given the maximum likelihood estimates of theta = 0.062 and phi = 0.938

(3) Constant	Cotton returns subjective mean	Cotton allotment indicator	Alfalfa returns subjective mean	Barley returns subjective mean	Barley program estimated participation	Subjective mean in 1949	Alfalfa returns subjective risk	R-SQR D-W
3511843.4	−1673.6201	206646.07	−28447.994	20834.054	−131813.86	−2967354.7	471.57006	0.8878
922762.0	1882.9675	37112.77	11781.046	19812.666	62899.13	932733.9	296.13269	1.7961

Cotton—Given the maximum likelihood estimate of theta = 0.876

(1) Constant	Cotton returns subjective mean	Cotton allotment indicator	Cotton allotment	Cotton price support	Cotton diversion	Subjective mean in 1949	R-SQR D-W
1080270.6	336.36169	−1072510.6	.74067245	379.86096	−.62415718	−173607.25	0.9682
87923.7	186.60665	134258.5	.17988352	508.31494	.36808853	88442.15	2.1659

TABLE 2—(*continued*)
ESTIMATED ACREAGE RELATIONSHIPS FOR THE SAN JOAQUIN VALLEY—(*continued*)

Rice—Given the maximum likelihood estimate of theta = 0.994

(1) Constant	Rice returns subjective mean	Rice allotment indicator	Rice allotment	Cotton returns subjective mean	Cotton allotment indicator	Cotton allotment	Subjective mean in 1949	R-SQR D-W
52807.855	47.357673	−92036.685	.80205261	−55.292167	64293.537	−.01814973	−18802.152	0.8293
13317.405	46.797912	16696.624	.25530693	33.941734	34458.479	.03927439	15440.315	1.9003

Sugar beets—Given the maximum likelihood estimate of theta = 0.735

(1) Constant	Cotton allotment indicator	Cotton allotment	Sugar beet returns subjective mean	Corn returns subjective mean	Corn support eligibility	Subjective mean in 1949	R-SQR D-W
66517.304	48555.326	−.08822814	736.23937	−1170.7233	−66083.821	57053.755	0.9085
40650.014	44642.762	.05746401	133.47674	341.7805	10654.730	33797.788	2.1867

Wheat—Given the maximum likelihood estimate of theta = 0.059

(1) Constant	Wheat returns subjective mean	Wheat program participation	Participating wheat allotment	Wheat support eligibility	Subjective mean in 1949	R-SQR D-W
−1369612.7	30941.042	−48847.474	.25791587	46389.350	1453022.4	0.7734
534412.6	10983.598	47661.399	.24015815	21042.008	516951.0	1.0805

Wheat—Given the maxiumum likelihood of theta = 0.070 and phi = 0.997

(2) Constant	Wheat returns subjective mean	Wheat program participation	Participating wheat allotment	Wheat support eligibility	Subjective mean in 1949	Subjective risk in 1949	Wheat returns subjective risk	R-SQR D-W
−122581.80	56237.449	−36157.426	.20099365	38489.826	2409732.3	−2170666.4	−50269.155	0.8862
4100214.4	31294.069	36942.176	.18630599	18305.568	1030607.4	3184882.4	27735.023	1.9479

Wheat—Given the maximum likelihood estimates of theta = 0.035 and phi = 0.965

(3) Constant	Wheat returns subjective mean	Wheat program participation	Participating wheat allotment	Wheat support eligibility	Subjective mean in 1949	Wheat returns subjective risk	R-SQR D-W
−3602852.3	90732.231	−31830.849	.17055964	14694.220	3769377.4	−3117.7558	0.8740
764017.3	18110.897	37037.434	.18668109	17384.018	770960.5	899.5445	1.7363

Alfalfa—Given the maximum likelihood estimate of theta = 0.994

(1) Constant	Cotton allotment indicator	Alfalfa returns subjective mean	Alfalfa acreage lag	Subjective mean in 1949	R-SQR D-W
262721.59	105297.85	704.51086	.25527629	−6516555.3	0.8969
78077.33	23450.82	226.52508	.14591037	4943430.3	1.4630

Corn—Given the maximum likelihood estimate of theta = 0.524

(1) Constant	Corn returns subjective mean	Cotton allotment indicator	Corn support eligibility	Corn-sorghum estimated participation	Subjective mean in 1949	R-SQR D-W
−249049.94	2649.0449	55913.085	30473.046	−41948.680	220957.64	0.9193
51717.07	334.9343	11562.402	14389.144	21803.073	35943.91	2.0926

Grain sorghum—Given the maximum likelihood estimate of theta = 0.071

(1) Constant	Cotton allotment indicator	Cotton allotment	Sorghum returns subjective mean	Corn-sorghum estimated participation	Sorghum support eligibility	Cotton price support	Subjective mean in 1949	R-SQR D-W
−82601.108	73057.460	−.05611376	3805.7626	−31879.701	31705.026	−234.54049	59640.445	0.9675
211045.68	37418.965	.05164697	2617.1015	18226.953	12342.254	128.14825	202494.46	2.9982

TABLE 2—(*continued*)
ESTIMATED ACREAGE RELATIONSHIPS FOR THE SAN JOAQUIN VALLEY—(*continued*)

Grain sorghum—Given the maximum likelihood estimates of theta = 0.240 and phi = 0.710

(2) Constant	Cotton allotment indicator	Cotton allotment	Sorghum returns subjective mean	Corn-sorghum estimated participation	Sorghum support eligibility	Cotton price support	Subjective mean in 1949	Subjective risk in 1949	Sorghum returns subjective risk	R-SQR D-W
−187719.34	93480.968	−.06924427	4469.1972	−30076.041	43463.067	−407.79711	224845.27	−74070.148	−296.61669	0.9731
148818.09	44638 652	.05975723	1578.0615	19797.126	17184.111	217.90136	269093.35	259912.87	120.24728	3.2253

Grain sorghum—Given he maximum likelihood estimates of theta = 0.241 and phi = 0.759

(3) Constant	Cotton allotment indicator	Cotton allotment	Sorghum returns subjective mean	Corn-sorghum estimated participation	Sorghum support eligibility	Cotton price support	Subjective mean in 1949	Sorghum returns subjective risk		R-SQR D-W
−180805.58	96334.533	−.07196194	4454.6708	−34172.834	46329.850	−407.53265	139923.60	−372.20397		0.9730
140240.36	43207.568	.05792462	1499.6044	19562.232	15689.517	177.27670	123368.75	142.61022		3.2525

*Coefficient estimates for the linear equations are given in the first line in each case with estimated standard errors in the second line. Units of measurement used for the respective variables can be found in Appendix C. Numbers in parentheses indicate the estimation model used.

TABLE 3
ESTIMATED ACREAGE RELATIONSHIPS FOR THE SACRAMENTO VALLEY

Barley—Given the maximum likelihood estimate of theta = 0.006*

(1) Constant	Barley returns subjective mean	Safflower returns subjective mean	Rice allotment indicator	Rice allotment	Barley program estimated participation	Subjective mean in 1949	R-SQR D-W
−4734661.8	116496.73	−41986.942	54727.897	−.20417041	−36793.378	5221855.9	0.9610
3697953.4	108072.35	32431.745	64095.821	.26236137	40057.592	3693824.0	2.5985

Rice—Given the maximum likelihood estimate of theta = 0.482

(1) Constant	Rice returns subjective mean	Rice allotment indicator	Rice allotment	Subjective mean in 1949	R-SQR D-W
298916.24	172.35418	−319589.34	.92385101	−23120.388	0.8851
31853.46	175.58978	41642.13	.16391979	38717.894	1.8700

Sugar beets—Given the maximum likelihood estimate of theta = 0.494

(1) Constant	Sugar beet returns subjective mean	Barley returns subjective mean	Corn returns subjective mean	Corn support eligibility	Barley program estimated participation	Subjective mean in 1949	R-SQR D-W
95359.916	132.08987	−506.91174	−241.53997	−11203.157	33153.171	−18552.675	0.7336
37327.551	120.60456	407.59222	165.99859	4840.410	11090.419	33716.964	2.3558

Sugar beets—Given the maximum likelihood estimates of theta = 0.588 and phi = 0.412

(2) Constant	Sugar beet returns subjective mean	Barley returns subjective mean	Corn returns subjective mean	Corn support eligibility	Barley program estimated participation	Subjective mean in 1949	Barley returns subjective risk	R-SQR D-W
83107.013	156.62991	−620.25622	−215.13333	−9293.0546	30008.296	−7888.8183	115.53977	0.8060
29309.099	89.51100	332.63977	124.79673	4134.0439	9930.998	26552.385	53.32453	2.7648

TABLE 3—(*continued*)
ESTIMATED ACREAGE RELATIONSHIPS FOR THE SACRAMENTO VALLEY—(*continued*)

Sugar beets—Given the maximum likelihood estimates of theta = 0.588 and phi = 0.412

(3) Constant	Sugar beet returns subjective mean	Barley returns subjective mean	Corn returns subjective mean	Corn support eligibility	Barley program estimated participation	Subjective mean in 1949	Barley returns subjective risk	R-SQR D-W
83106.994	156.63006	−620.25622	−215.13333	−9293.0507	30008.292	−7888.7724	115.53987	0.8060
29309.089	89.51098	332.63970	124.79670	4134.0429	9930.994	26552.375	53.32451	2.7648

Wheat—Given the maximum likelihood estimates of theta = 0.020 and phi = 0.980

(2) Constant	Wheat program participation	Participating wheat allotment	Wheat returns subjective mean	Subjective mean in 1949	Wheat returns subjective risk	R-SQR D-W
−4521675.4	−138405.60	.91854568	92434.177	4645512.6	−2193.3593	0.8610
1626242.2	22802.96	.18638751	29643.568	1632206.0	553.5104	2.2958

Wheat—Given the maximum likelihood estimates of theta = 0.020 and phi = 0.980

(3) Constant	Wheat program participation	Participating wheat allotment	Wheat returns subjective mean	Subjective mean in 1949	Wheat returns subjective risk	R-SQR D-W
−4521675.4	−138405.60	.91854568	92434.177	4645512.6	−2193.3593	0.8610
1626242.2	22802.96	.18638751	29643.568	1632206.0	553.5104	2.2958

Alfalfa—Given the maximum likelihood estimate of theta = 0.488

(1) Constant	Alfalfa returns subjective mean	Rice allotment indicator	Rice allotment	Subjective mean in 1949	Dummy variable for 1958	R-SQR D-W
73762.540	280.02307	37623.147	−.09306851	9655.0605	−14572.450	0.7641
13629.264	106.08972	8969.009	.03098923	17088.588	4857.478	1.5697

Alfalfa—Given the maximum likelihood estimates of theta = 0.630 and phi = 0.450

(2) Constant	Alfalfa returns subjective mean	Rice allotment indicator	Rice allotment	Subjective mean in 1949	Subjective risk in 1949	Alfalfa returns subjective risk	Dummy variable for 1958	R-SQR D-W
92964.496	197.00054	29844.683	−.09168659	327641.67	−278029.86	−3.9921177	−15537.948	0.8074
14223.534	86.41261	10730.383	.03025824	275842.66	227214.43	2.9115841	4779.262	1.5095

Alfalfa—Given the maximum likelihood estimates of theta = 0.500 and phi = 0.500

(3) Constant	Alfalfa returns subjective mean	Rice allotment indicator	Rice allotment	Subjective mean in 1949	Alfalfa returns subjective risk	Dummy variable for 1958	R-SQR D-W
80474.548	259.82269	36986.574	−.09957919	2715.5371	−4.6478146	−15569.205	0.7929
13743.814	101.46141	8701.044	.03038574	17061.087	3.3332018	4765.560	1.5516

Corn—Given the maximum likelihood estimate of theta = 0.229

(1) Constant	Corn returns subjective mean	Corn support eligibility	Corn-sorghum estimated participation	Wheat program participation	Subjective mean in 1949	R-SQR D-W
−247222.82	2236.9018	12276.599	−22325.486	24775.829	232355.07	0.9685
31226.20	211.6088	4136.250	8618.419	3827.007	28793.63	1.9510

Grain sorghum—Given the maximum likelihood estimate of theta = 0.088

(1) Constant	Barley returns subjective mean	Sorghum returns subjective mean	Corn-sorghum estimated participation	Subjective mean in 1949	R-SQR D-W
53792.733	−12497.143	8189.9492	−49630.869	−15749.220	0.9130
99967.210	3569.796	2661.4438	14530.405	104934.84	2.2588

TABLE 3—(*continued*)
ESTIMATED ACREAGE RELATIONSHIPS FOR THE SACRAMENTO VALLEY—(*continued*)

Grain sorghum—Given the maximum likelihood estimates of theta = 0.260 and phi = 0.610

(2) Constant	Barley returns subjective mean	Sorghum returns subjective mean	Corn-sorghum estimated participation	Subjective mean in 1949	Subjective risk in 1949	Barley returns subjective risk	Sorghum returns subjective risk	R-SQR D-W
−81528.701	−4290.5966	4741.8593	−32009.563	153974.83	−37392.801	204.53237	−183.20053	0.9283
60674.552	1740.8747	1395.2573	15103.533	132027.68	83665.504	132.14941	63.48562	2.3605

Grain sorghum—Given the maximum likelihood estimates of theta = 0.276 and phi = 0.724

(3) Constant	Barley returns subjective mean	Sorghum returns subjective mean	Corn-sorghum estimated participation	Subjective mean in 1949	Barley returns subjective risk	Sorghum returns subjective risk	R-SQR D-W
−44261.569	−3889.2055	4134.6943	−37405.075	79457.052	217.57388	−234,37442	0.9275
39870.146	1409.1411	887.5587	14972.331	42972.278	167.21978	65.40481	2.3555

*Coefficient estimates for the linear equations are given in the first line in each case with estimated standard errors in the second line. Units of measurement used for the respective variables can be found in Appendix C. Numbers in parentheses indicate the estimation model used.

TABLE 4
ESTIMATED ACREAGE RELATIONSHIPS FOR SOUTHERN CALIFORNIA

Barley—Given the maximum likelihood estimate of theta = 0.571*

(1) Constant	Barley returns subjective mean	Alfalfa returns subjective mean	Cotton allotment indicator	Barley support eligibility	Subjective mean in 1949	R-SQR D-W
88956.355	3520.4692	−1217.9829	28560.970	102536.50	−49546.679	0.7384
51554.269	1724.4155	538.4989	18259.845	19984.45	43680.219	1.7157

Barley—Given the maximum likelihood estimates of theta = 0.140 and phi = 0.880

(2) Constant	Barley returns subjective mean	Alfalfa returns subjective mean	Cotton allotment indicator	Barley support eligibility	Subjective mean in 1949	Subjective risk in 1949	Alfalfa returns subjective risk	R-SQR D-W
−370544.28	20011.730	−5596.1171	39042.490	51512.460	−2986398.9	3463226.9	97.107910	0.8959
237161.94	5415.354	2017.2863	14011.931	16232.404	632824.3	841226.1	76.863494	2.6128

Barley—Given the maximum likelihood estimates of theta = 0.106 and phi = 0.894

(3) Constant	Barley returns subjective mean	Alfalfa returns subjective mean	Cotton allotment indicator	Barley support eligibility	Subjective mean in 1949	Alfalfa returns subjective risk	R-SQR D-W
865649.87	8584.1562	−11795.997	42664.193	53296.909	−744038.54	345.71173	0.7845
218593.33	7716.4238	4105.708	19328.224	22945.312	207694.28	94.46719	1.9753

Cotton

(1) Constant	Cotton allotment indicator	Cotton allotment	Cotton price support	Dummy variable for 1949	Dummy variable for 1951	Dummy variable for 1952	R-SQR D-W
134953.57	−160792.00	.92732009	175.40075	−132354.52	−104653.98	−38052.653	0.9825
7947.66	7393.58	.07344641	37.12120	8774.23	7208.71	7207.969	2.0894

TABLE 4—(*continued*)
ESTIMATED ACREAGE RELATIONSHIPS FOR SOUTHERN CALIFORNIA—(*continued*)

Sugar beets—Given the maximum likelihood estimates of theta = 0.540 and phi = 0.950

(2) Constant	Sugar beet returns subjective mean	Sugar beet share indicator	Flaxseed returns subjective mean	Alfalfa returns subjective mean	Subjective mean in 1949	Subjective risk in 1949	Sugar beet returns subjective risk	Flaxseed returns subjective risk	Alfalfa returns subjective risk	R-SQR D-W
142421.24	77.187484	−8191.3886	−283.52264	−299.87164	−12478.127	−86401.233	−60.531173	126.48010	51.314140	0.9034
38354.55	96.247238	4352.0273	148.53207	137.96939	24532.246	32391.514	22.200614	34.97721	44.789443	2.6001

Sugar beets—Given the maximum likelihood estimates of theta = 0.059 and phi = 0.941

(3) Constant	Sugar beet returns subjective mean	Sugar beet share indicator	Flaxseed returns subjective mean	Alfalfa returns subjective mean	Subjective mean in 1949	Sugar beet returns subjective risk	Flaxseed returns subjective risk	Alfalfa returns subjective risk	R-SQR D-W
72084.416	5295.5537	−6073.0888	−7655.0117	−4607.7460	−26270.484	−28.443328	144.42346	64.705123	0.8863
218887.55	1420.2224	4561.4335	3792.2402	3581.4990	222103.99	8.251462	56.62250	64.541458	1.4398

Wheat—Given the maximum likelihood estimate of theta = 0.259

(1) Constant	Wheat returns subjective mean	Wheat program participation	Participating wheat allotment	Subjective mean in 1949	Dummy variable for 1962	Dummy variable for 1970	R-SQR D-W
−45997.685	2875.5327	−73946.170	.98604293	116738.96	34881.714	78474.091	0.9466
21718.878	561.6350	19183.837	.24024848	21726.15	6884.109	6593.881	2.7312

Alfalfa—Given the maximum likelihood estimate of theta = 0.806

(1) Constant	Barley returns subjective mean	Alfalfa returns subjective mean	Alfalfa acreage lag	Subjective mean in 1949	Dummy variable for 1955	R-SQR D-W
124006.84	−1568.6845	418.75659	.61575370	86904.296	91766.643	0.9288
46057.56	491.7720	167.99060	.10994071	82270.106	11426.574	2.0904

Corn—Given the maximum likelihood estimate of theta = 0.318

(1) Constant	Corn returns subjective mean	Corn-sorghum estimated participation	Alfalfa returns subjective mean	Subjective mean in 1949	Dummy variable for 1954	R-SQR D-W
4704.8242	63.419113	−5315.6425	−57.282333	−5009.9619	8914.2148	0.8132
6422.2529	66.692886	2952.8305	19.610004	6803.2333	1818.9926	1.4786

Grain sorghum—Given the maximum likelihood estimate of theta = 0.123

(1) Constant	Sorghum returns subjective mean	Corn-sorghum estimated participation	Sugar beet returns subjective mean	Subjective mean in 1949	R-SQR D-W
−288303.33	8785.2656	−29.460586	−917.83789	311575.35	0.8237
225348.16	1351.5305	39746.597	858.72790	235332.75	0.9974

Grain sorghum—Given the maximum likelihood estimates of theta = 0.250 and phi = 0.890

(2) Constant	Sorghum returns subjective mean	Corn-sorghum estimated participation	Sugar beet returns subjective mean	Subjective mean in 1949	Subjective risk in 1949	Sorghum returns subjective risk	R-SQR D-W
120378.66	4020.1933	−83783.454	−923.82348	150713.99	−241036.64	−175.59283	0.8905
227064.58	1501.8015	38175.663	473.58636	118918.51	142313.07	173.55563	1.8398

Grain sorghum—Given the maximum likelihood estimates of theta = 0.271 and phi = 0.729

(3) Constant	Sorghum returns subjective mean	Corn-sorghum estimated participation	Sugar beet returns subjective mean	Subjective mean in 1949	Sorghum returns subjective risk	R-SQR D-W
−149794.21	6117.1464	−65910.529	−692.38391	178148.42	−170.20184	0.8824
87919.54	662.4633	34960.755	321.89752	95521.77	47.80697	1.7797

*Coefficient estimates for the linear equations are given in the first line in each case with estimated standard errors in the second line. Units of measurement used for the respective variables can be found in Appendix C. Numbers in parentheses indicate the estimation model used.

TABLE 5
ESTIMATED ACREAGE RELATIONSHIPS FOR THE CENTRAL COAST

Barley—Given the maximum likelihood estimate of theta = 0.006*

(1) Constant	Barley returns subjective mean	Wheat program participation	Subjective mean in 1949	R-SQR D-W
−2097490.8	48256.205	59781.091	2279657.8	0.6190
1895506.5	51625.499	12102.958	1894858.7	1.0804

Barley—Given the maximum likelihood estimates of theta = 0.020 and phi = 0.920

(2) Constant	Barley returns subjective mean	Wheat program participation	Subjective mean in 1949	Subjective risk in 1949	Barley returns subjective risk	R-SQR D-W
−2726515.5	61765.508	33697.285	3352439.5	−469644.24	−534.14477	0.8627
1133906.7	31387.843	9246.365	1212778.9	100669.49	526.92285	2.1015

Cotton—Given the maximum likelihood estimate of theta = 0.953

(1) Constant	Cotton returns subjective mean	Cotton allotment indicator	Cotton allotment	Wheat returns subjective mean	Wheat program participation	Wheat support eligibility	Subjective mean in 1949	R-SQR D-W
787.97338	.70286529	−1135.1821	.40731414	−6.0709848	686.92517	−110.62100	−378.52374	0.8222
243.17550	.21548351	429.2518	.21734191	2.4435443	403.83673	76.85417	137.79013	2.2213

Sugar beets—Given the maximum likelihood estimates of theta = 0.610 and phi = 0.990

(2) Constant	Sugar beet returns subjective mean	Sugar beet share indicator	Wheat program participation	Participating wheat allotment	Wheat support eligibility	Subjective mean in 1949	Subjective risk in 1949	Sugar beet returns subjective risk	R-SQR D-W
−174046.28	258.02593	−16719.443	38184.995	−.18007499	−31401.138	48420.990	221902.69	−127.69612	0.7924
110790.78	66.22964	3219.965	18563.724	.11885005	7821.425	16866.288	124174.17	35.25375	2.0538

Wheat

(1) Constant	Wheat program participation	Participating wheat allotment	Wheat support eligibility	R-SQR D-W
90507.831	−158680.05	.86195465	30841.202	0.9067
15278.537	24716.55	.18296290	6614.243	2.3448

Alfalfa—Given the maximum likelihood estimate of theta = 0.606

(1) Constant	Alfalfa returns subjective mean	Wheat program participation	Subjective mean in 1949	R-SQR D-W
39162.410	17.741298	1950.6000	−12006.563	0.6102
3536.968	26.456192	942.4211	6121.179	2.0224

Corn—Given the maximum likelihood estimate of theta = 0.024

(1) Constant	Corn returns subjective mean	Corn-sorghum estimated participation	Subjective mean in 1949	R-SQR D-W
−30436.072	589.94567	−3270.1323	32633.952	0.7989
26947.192	288.42346	1754.9538	27430.033	1.4654

Corn—Given the maximum likelihood estimates of theta = 0.440 and phi = 0.470

(2) Constant	Corn returns subjective mean	Corn-sorghum estimated participation	Subjective mean in 1949	Subjective risk in 1949	Corn returns subjective risk	R-SQR D-W
−8618.6093	173.02639	−3020.2329	22299.675	−11116.990	−1.2928211	0.8645
2319.8041	26.34870	1373.3208	13258.466	12234.034	.2590372	1.8449

Corn—Given the maximum likelihood estimates of theta = 0.488 and phi = 0.512

(3) Constant	Corn returns subjective mean	Corn-sorghum estimated participation	Subjective mean in 1949	Corn returns subjective risk	R-SQR D-W

TABLE 5—(*continued*)
ESTIMATED ACREAGE RELATIONSHIPS FOR THE CENTRAL COAST—(*continued*)

−6672.9882	153.84185	−3325.4726	9565.8496	−1.2979092	0.8544
1815.8657	21.62319	1410.9919	2259.9331	.2209877	1.7390

Grain sorghum—Given the maximum likelihood estimate of theta = 0.006

(1) Constant	Sorghum returns subjective mean	Subjective mean in 1949	R-SQR D-W
−45718.459	1125.5004	47752.818	0.7826
49828.298	666.9478	50208.320	1.8548

Grain sorghum—Given the maximum likelihood estimates of theta = 0.132 and phi = 0.868

(2) Constant	Sorghum returns subjective mean	Subjective mean in 1949	Sorghum returns subjective risk	R-SQR D-W
−5418.0166	179.80654	7526.8134	−11.061151	0.7956
2357.2636	37.73862	2717.1665	4.785008	1.9335

Grain sorghum—Given the maximum likelihood estimates of theta = 0.132 and phi = 0.868

(3) Constant	Sorghum returns subjective mean	Subjective mean in 1949	Sorghum returns subjective risk	R-SQR D-W
−5418.0166	179.80654	7526.8134	−11.061151	0.7956
2357.2636	37.73862	2717.1665	4.785008	1.9335

*Coefficient estimates for the linear equations are given in the first line in each case with estimated standard errors in the second line. Units of measurement used for the respective variables can be found in Appendix C. Numbers in parentheses indicate the estimation model used.

TABLE 6
ESTIMATED ACREAGE RELATIONSHIPS FOR THE MOUNTAIN REGION

Barley—Given the maximum likelihood estimates of theta = 0.320 and phi = 0.840*

(2) Constant	Barley returns subjective mean	Alfalfa returns subjective mean	Subjective mean in 1949	Subjective risk in 1949	Barley returns subjective risk	Alfalfa returns subjective risk	Dummy variable for 1956	R-SQR D-W
4401.6191	200.18530	−131.43777	−14243.015	18003.260	−30.577629	14.398166	3093.2539	0.9574
3307.7534	52.95093	52.74381	8491.267	7067.405	12.325925	10.613931	670.1671	2.5091

Barley—Given the maximum likelihood estimates of theta = 0.206 and phi = 0.794

(3) Constant	Barley returns subjective mean	Alfalfa returns subjective mean	Subjective mean in 1949	Barley returns subjective risk	Alfalfa returns subjective risk	Dummy variable for 1956	R-SQR D-W
8407.7109	298.04663	−241.13165	−136.95101	−11.464881	21.296646	3047.1093	0.9464
5668.6386	96.90443	95.00602	5666.2148	4.270287	3.723736	685.9249	2.2537

Rice—Given the maximum likelihood estimate of theta = 0.488

(1) Constant	Wheat returns subjective mean	Wheat program participation	Rice returns subjective mean	Rice allotment indicator	Rice allotment	Subjective mean in 1949	R-SQR D-W
7610.7695	−84.161392	2489.7568	9.3372478	−5712.8906	.31723999	−3647.3559	0.8003
2372.7006	36.933486	827.8066	7.5461616	1451.7258	.25936019	2802.5610	1.6897

Rice—Given the maximum likelihood estimates of theta = 0.580 and phi = 0.160

(2) Constant	Wheat returns subjective mean	Wheat program participation	Rice returns subjective mean	Rice allotment indicator	Rice allotment	Subjective mean in 1949	Subjective risk in 1949	Wheat returns subjective risk	R-SQR D-W
9527.5410	−124.96388	3168.2993	4.3002853	−6468.8164	.35494407	−7822.5126	2401.6938	4.1420106	0.8476
3064.1655	45.46625	854.4088	8.7089042	1836.8034	.33504295	7460.0302	4987.2539	2.1351361	2.2083

TABLE 6—(*continued*)
ESTIMATED ACREAGE RELATIONSHIPS FOR THE MOUNTAIN REGION—(*continued*)

Rice—Given the maximum likelihood estimates of theta = 0.606 and phi = 0.394

(3) Constant	Wheat returns subjective mean	Wheat program participation	Rice returns subjective mean	Rice allotment indicator	Rice allotment	Subjective mean in 1949	Wheat returns subjective risk	R-SQR D-W
8716.0488	−110.86309	3159.5327	5.1760549	−7229.3964	.50312019	−4679.8339	5.4554452	0.8357
2109.7846	36.73594	833.1707	6.5637178	1441.8806	.23842739	2420.5214	3.0015835	2.1572

Wheat

(1) Constant	Wheat program participation	Participating wheat allotment	Rice allotment indicator	Rice allotment	Wheat support eligibility	R-SQR D-W
12714.011	−16509.806	.72717391	5640.3457	−.90153991	2221.6704	0.9253
1545.965	1938.595	.12971187	2551.5747	.37363624	690.9913	2.0214

Alfalfa—Given the maximum likelihood estimate of theta = 0.006

(1) Constant	Barley returns subjective mean	Alfalfa acreage lag	Subjective mean in 1949	Dummy variable for 1955	Dummy variable for 1956	R-SQR D-W
64974.421	−2138.7392	1.0290307	−64503.698	601.20727	716.50183	0.8518
53320.073	1627.9440	.1201238	53248.624	376.84924	399.15924	2.3685

Alfalfa—Given the maximum likelihood estimates of theta = 0.020 and phi = 0.990

(2) Constant	Barley returns subjective mean	Alfalfa acreage lag	Subjective mean in 1949	Subjective risk in 1949	Barley returns subjective risk	Dummy variable for 1955	Dummy variable for 1956	R-SQR D-W
−59482.201	−273.18609	.72802520	−91914.920	153259.83	3.3581952	452.27783	548.85339	0.8690
65891.666	726.36206	.27637080	56641.435	118488.55	156.92108	480.78613	475.60540	2.0289

Alfalfa—Given the maximum likelihood estimates of theta = 0.009 and phi = 0.991

(3) Constant	Barley returns subjective mean	Alfalfa acreage lag	Subjective mean in 1949	Barley returns subjective risk	Dummy variable for 1955	Dummy variable for 1956	R-SQR D-W
56305.674	−1941.2167	.94020126	−56009.549	83.468902	708.82360	594.78295	0.8540
44997.233	1524.5507	.21900772	45134.009	167.96722	441.27056	479.27655	2.2698

Corn—Given the maximum likelihood estimate of theta = 0.582

(1) Constant	Corn returns subjective mean	Corn-sorghum estimated participation	Subjective mean in 1949	R-SQR D-W
142.16336	.89567657	−249.90093	164.08148	0.7975
26.37492	.50190872	36.31717	53.81669	2.3950

Corn—Given the maximum likelihood estimates of theta = 0.523 and phi = 0.477

(3) Constant	Corn returns subjective mean	Corn-sorghum estimated participation	Subjective mean in 1949	Corn returns subjective risk	R-SQR D-W
163.55203	.42528366	−204.47409	134.49130	−.01952452	0.8134
34.05614	.67676208	50.92565	58.71327	.01564387	2.2326

Grain sorghum—Given the maximum likelihood estimate of theta = 0.165

(1) Constant	Sorghum returns subjective mean	Corn-sorghum estimated participation	Subjective mean in 1949	R-SQR D-W
−955.66918	27.581302	−501.52880	1070.8703	0.9404
246.83001	3.926590	107.72128	289.1727	2.3382

Grain sorghum—Given the maximum likelihood estimates of theta = 0.190 and phi = 0.780

Sorghum returns subjective	Corn-sorghum estimated	Subjective mean	Subjective risk	Sorghum returns subjective	R-SQR

TABLE 6—(*continued*)
ESTIMATED ACREAGE RELATIONSHIPS FOR THE MOUNTAIN REGION—(*continued*)

(2) Constant	mean	participation	in 1949	in 1949	risk	D-W
−618.84521	23.553043	−534.01464	−709.49877	1449.5439	−.21895114	0.9412
1085.7514	13.637094	159.92944	6192.2148	5151.4355	.34624900	2.3305

Grain sorghum—Given the maximum likelihood estimates of theta = 0.194 and phi = 0.806

(3) Constant	Sorghum returns subjective mean	Corn-sorghum estimated participation	Subjective mean in 1949	Sorghum returns subjective risk	R-SQR D-W
−919.16223	27.257610	−521.97241	1033.5749	−.27638529	0.9408
220.96066	3.846700	151.07217	264.9544	.37496795	2.3032

*Coefficient estimates for the linear equations are given in the first line in each case with estimated standard errors in the second line. Units of measurement used for the respective variables can be found in Appendix C. Numbers in parentheses indicate the estimation model used.

TABLE 7
ESTIMATED ACREAGE RELATIONSHIPS FOR NORTHERN CALIFORNIA

Barley—Given the maximum likelihood estimate of theta = 0.170*

(1) Constant	Wheat returns subjective mean	Wheat program participation	Subjective mean in 1949	R-SQR D-W
49171.083	−58.647918	17715.837	59972.380	0.8145
18288.771	305.32446	6120.040	20982.370	1.5476

Barley—Given the maximum likelihood estimates of theta = 0.070 and phi = 0.580

(2) Constant	Wheat returns subjective mean	Wheat program participation	Subjective mean in 1949	Subjective risk in 1949	Wheat returns subjective risk	R-SQR D-W
136332.79	−1949.6171	10774.950	−67715.586	50643.863	8.9748362	0.9129
45694.66	826.8508	4800.166	52896.508	12051.117	3.3022651	2.3913

Barley—Given the maximum likelihood estimates of theta = 0.203 and phi = 0.797

(3) Constant	Wheat returns subjective mean	Wheat program participation	Subjective mean in 1949	Wheat returns subjective risk	R-SQR D-W
90489.902	−1059.1347	16768.840	18235.794	45.710510	0.8450
23207.592	535.0698	5668.776	25895.470	24.252445	1.8709

Wheat

(1) Constant	Wheat program participation	Participating wheat allotment	Wheat support eligibility	R-SQR D-W
32926.487	−69417.056	.78752822	16254.631	0.9290
4710.547	10793.411	.18529536	2076.429	2.4991

TABLE 7—(*continued*)
ESTIMATED ACREAGE RELATIONSHIPS FOR NORTHERN CALIFORNIA—(*continued*)

Alfalfa—Given the maximum likelihood estimate of theta = 0.006

(1) Constant	Alfalfa returns subjective mean	Alfalfa acreage lag	Subjective mean in 1949	R-SQR D-W
−1355314.2	24968.713	.64286544	1378345.9	0.8616
1355377.5	21751.131	.19436637	1355697.0	2.1442

Alfalfa—Given the maximum likelihood estimates of theta = 0.580 and phi = 0.985

(2) Constant	Alfalfa returns subjective mean	Alfalfa acreage lag	Subjective mean in 1949	Subjective risk in 1949*	Alfalfa returns subjective risk	R-SQR D-W
237901.57	474.40985	.44942932	38706.121	−225189.20	−1327.9494	0.9239
65821.25	198.95404	.16331684	23771.972	56411.70	509.8107	2.7704

Alfalfa—Given the maximum likelihood estimates of theta = 0.018 and phi = 0.982

(3) Constant	Alfalfa returns subjective mean	Alfalfa acreage lag	Subjective mean in 1949	Alfalfa returns subjective risk	R-SQR D-W
−1370581.6	26159.061	.59853370	1404174.4	−1347.7280	0.8950
563787.4	9932.177	.17178215	567794.3	578.8747	2.4696

*Coefficient estimates for the linear equations are given in the first line in each case with estimated standard errors in the second line. Units of measurement used for the respective variables can be found in Appendix C. Numbers in parentheses indicate the estimation model used.

Impact of Government Programs and Importance of Risk in Acreage Response

Because a wide variety of government programs have been offered in California, implications for several alternative forms of government intervention might be drawn from the results. For example, cotton and rice have been subject to strict allotments (that is, allotments with marketing quotas) while for example the feed grains have been controlled only by voluntary allotments with price supports. Alfalfa has had no program at all. In the case of wheat, programs have ranged from price-support operations only all the way to strict allotments with marketing quotas, thus creating an interesting observation on the effects of variation in government programs. Finally, in the case of sugar beets, grower income is not maintained by CCC purchases and loans but through direct payments to growers in the form of subsidies.

Effects of strict control: the cases of cotton and rice. Apparently, cotton and rice programs have been the dominant forces in the San Joaquin Valley and Sacramento Valley, respectively. As both are probably among the most profitable field crops in the state, allotments are essentially always filled. In both the San Joaquin and Imperial valleys, the major determinant of cotton acreage response appears to be the cotton allotment although income considerations have also been of some importance in the San Joaquin Valley. Allotments have been the sole dominating factor in the Imperial Valley since 1954. The huge increase in acreage prior to 1954 (handled through the introduction of shift variables) was a result of the development of new measures of insect control for Imperial Valley cotton.

In each of these major cotton-producing districts, cotton allotments have also been important indirect influences on many other important field crops. In the San Joaquin Valley, the acreages of barley, rice, sugar beets, alfalfa, corn, and grain sorghum were all significantly affected by cotton allotments.[61]

Rice allotments have had similar effects in the Sacramento Valley as the major crops grown in the central part of the Valley (barley, rice, and alfalfa) are all significantly dependent on the allotments. In the San Joaquin Valley, where rice is relatively much less important, cotton variables have also been of some importance. Other crops in the San Joaquin Valley do not seem to be affected much by rice allotments because of the relative unimportance of rice there.

Apparently, strict controls can be less important when the controlled crops are not among the most profitable production alternatives available. For both cotton in the central coast and rice in the mountain regions, where production is said to be relatively less profitable, direct controls have been relatively less important and variables relating directly to other crops have been of greater importance.

Risk can not be indicated to be an important factor for any of the crops controlled by strict allotments except for rice in the Mountain Region which is relatively unimportant. Apparently, prices have been stabilized or held high enough by restrictive measures and price-support operations so that risk is no longer of importance. In the case of cotton, price supports have apparently been partly responsible, while prices for rice seem to have been maintained high enough by restrictive measures so that the price-support level has had very little importance.

Some important aspects of the cotton program have not been included in this analysis, as sufficient data were not available to undertake a complete analysis of the cotton export program. Lack of data has also prevented the estimation of response to the cotton diversion program, although that activity seems to have been of importance in the San Joaquin Valley.

[61] Although for rice and grain sorghum neither of the two cotton allotment variables appear significant in some cases, much more importance is indicated when only one of the variables is introduced separately.

Effects of voluntary control: the feed grains. Casual observation of the field-crop sector might lead one to conclude that the voluntary controls set up for the feed grains in the 1960's have had almost no effect in California except, perhaps, in the case of barley. The acreages of both corn and sorghum increased greatly soon after the implementation of the feed grains program in 1961 (figs. 5 and 6). As acreage in the midwest contracted, demand for California feed grains by the California livestock sector increased, resulting in high prices. Increased yields with new varieties, in conjunction with high prices, then induced a large shift toward corn and sorghum production in California. Apparently, the shift may have been substantially greater had the feed grain programs not been implemented. For example, the estimated relationships indicate that the acreage of corn in the San Joaquin Valley would have been 40 per cent higher in 1961, the first year of the program, had the voluntary allotments not been established. In the Sacramento Valley, corn acreage would have been 35 per cent higher. Results also indicate that grain sorghum in southern California would have doubled its observed acreage in 1961 had the program not been in effect.

For the late 1960's, effects appear somewhat less as the rate of participation was often much lower. By 1970 estimates indicate that corn acreages would have been only 15 per cent higher in the San Joaquin Valley and 20 per cent higher in the Sacramento Valley. Sorghum acreage in southern California and the Sacramento Valley would have been only 20 per cent greater had the programs not been in effect.

Although the barley program is of evident significance in the San Joaquin and Sacramento valleys, its effectiveness in terms of estimated percentage acreage reduction is far less. Apparently, much of the reduction in barley acreage would have been forthcoming regardless of the implementation of restricting programs. As many new varieties have been increasing the yields of competing crops, barley has been gradually losing its competitive position. However, some new barley varieties have been coming into use in the early 1970's, and may alter the situation.

Price-support levels for feed grains are also evidently not often of importance. The huge feed grain demand seems to have sustained prices at high enough levels to reduce the effectiveness of CCC transactions for California feed grains.

Although data sufficient to allow the estimation of decision-makers' response to the voluntary programs and diversion possibilities were not available, an attempt was made to isolate the effect of the diversion programs by including diversion variables. Due to the restrictions set on minimum and maximum diversion percentages, the participation and diversion variables were too highly correlated to allow the distinction. Hence, the effects of diversion possibilities as well as program participation are jointly carried in the coefficients of participation.

The wheat program. The estimation of response to wheat program controls has indeed presented an interesting problem since three major forms of the program have been offered during different parts of the period of investigation. Evidently, the effectiveness of the allotments did not change considerably when marketing quotas were dropped in 1964. To distinguish response to voluntary allotments from response to strict allotments, a separate variable was first included for participation in the voluntary allotments (in addition to the variable used for participation in either strict or voluntary allotments). Resulting estimates indicated, however, that structural change in response had not taken place as the extra participation variable was not significant in any estimated models in any district. It was therefore concluded that response on participating farms was unchanged with the relaxation of marketing quotas so that only one participation variable was used in the equations reported in tables 2 through 7.

Although wheat allotments have not been nearly filled in recent years in California, results indicate in every case that acreage has been highly dependent on the allotment controls established. Furthermore, estimates indicate that, even at the margin, 79 to 99 per cent of any increase in allotments would be planted to wheat in every district except the San Joaquin Valley. Apparently, wheat production in California is not generally profitable enough to expand acreage beyond allotments when price-support eligibility is thus lost. The role of wheat in irrigated areas has been changing rapidly as a result of the introduction of Mexican varieties, however, and associated changes in the effectiveness of government programs are not yet certain.

Interestingly, wheat appears to have played quite a different role in the mountain and coastal areas of the state as opposed to the irrigated valleys. In the irrigated valleys, many more profitable production alternatives exist, and many other crops are thus of greater importance than wheat. Consequently, in these areas wheat controls have had little effect on the acreages of most other crops. In the Sacramento and San Joaquin valleys, risk associated with wheat production also becomes of importance in the acreage response of wheat due to the competitive position of other crops.

In the northern, mountain, and coastal areas wheat is one of the most profitable crops. Thus, the influence of wheat controls is more evident in the acreages of other crops. In San Luis Obispo County, the major wheat area in the central coast, and in northern California, wheat is evidently the most profitable crop. In both areas it appears that acreage decisions for other crops are largely, if not solely, dependent on variables related directly to wheat production. For example, in northern California where quite a large acreage seems to have really only two alternatives—wheat and barley—variables related directly to barley were not important in barley acreage response.

As in the feed grains program, data were not sufficient to allow estimation of response to voluntary allotment programs and diversion possibilities. The inclusion of diversion variables also failed to reveal significant effects in acreage response.

The sugar beet program. Although sugar beet acreage is influenced by what might be characterized as strict controls since the industry operates under a contract system, many other influences are also important. Evidently, sugar beet production is not as profitable as cotton and rice production in their respective areas. Hence, acreage is somewhat less responsive to controls and more responsive to forces relating directly to other crops. Corn and barley seem to be the important competing crops in the Central Valley. The imposition of cotton allotments also appears to have had some effect in the San Joaquin Valley. Although sugar beets replaced much of the flaxseed acreage in southern California during the 1950's, alfalfa has evidently been the major competing crop there in recent years. Wheat is the most important field crop alternative in the Central Coast.

While the risk associated with sugar beet production does not appear important in the Central Valley, the reason probably is that risk has not been changing rapidly or that farmers have regarded it as fixed. As indicated in (1.15), when risk is constant and known the applicable econometric model excludes risk. However, sugar beets are generally regarded as a high-risk crop (table 8). Risk seems to be of reasonable significance both in the Central Coast and in southern California. In southern California reasonable results could not be obtained without its inclusion.

Although proportionate shares were established statewide for 1955 through 1960, 1965, and 1966, the estimated equations indicate that much reduction in acreage would have occurred anyway in the Central Valley due to the changes in factors relating to competing crops. In southern California and especially in the Central Coast, where production alternatives are more limited, the shares seem to have had

TABLE 8
FARMER'S SUBJECTIVE MEAN AND VARIANCE OF RETURNS BEFORE AND AFTER THE IMPLEMENTATION OF RESTRICTING PROGRAMS

Crop and district	1954		1970	
	Mean	Variance	Mean	Variance
Barley				
San Joaquin	36.46	357.86	44.16	336.50
Sacramento	32.83	201.03	34.16	205.94
Southern	34.26	168.49	55.35	153.70
Central coast	28.76	153.84	31.03	114.78
Mountain	36.13	194.94	37.31	43.35
Northern	48.35	442.82	54.93	132.07
Cotton*				
San Joaquin	196.19	508.95	212.17	1977.45
Southern	273.81	18145.89	346.63	14537.86
Central coast	113.51	940.28	134.31	1625.79
Rice				
San Joaquin	161.49	4685.51	251.55	75.03
Sacramento	168.94	1586.28	263.64	319.04
Mountain	183.25	2130.04	256.92	465.48
Sugar beets†				
San Joaquin	257.21	308.72	340.10	1302.13
Sacramento	266.62	1368.57	298.83	2421.89
Southern	267.97	1254.68	333.93	1473.25
Central coast	307.61	1822.91	394.66	1999.27
Wheat				
San Joaquin	34.34	122.23	44.14	121.66
Sacramento	41.82	212.65	48.19	237.99
Southern	38.63	132.82	33.74	42.50
Central coast	33.22	68.37	26.15	103.70
Mountain	31.45	15.93	32.56	141.32
Northern	35.49	29.17	50.90	152.50
Alfalfa				
San Joaquin	108.09	2672.32	160.97	70.96
Sacramento	118.78	1316.86	149.76	141.07
Southern	103.47	1826.48	183.33	144.48
Central coast	114.78	1303.72	145.48	53.20
Mountain	68.88	286.69	70.44	259.32
Northern	62.10	264.29	72.39	222.77
Corn				
San Joaquin	73.38	242.46	121.99	169.68
Sacramento	97.90	994.54	137.79	336.36
Southern	101.91	1130.46	92.23	131.70
Central coast	90.74	1608.62	112.11	75.27
Mountain	29.73	23.36	77.02	27.97
Grain sorghum				
San Joaquin	58.15	129.64	83.33	60.84
Sacramento	74.94	204.68	94.41	58.38
Southern	62.10	385.84	79.63	182.37
Central coast	46.95	218.89	69.68	321.88
Mountain	46.21	325.78	75.10	112.22

*Excludes cottonseed.
†Includes Government payments to producers.

a much greater effect.[62] Estimates indicate that the Central Coast acreage would have been 60 per cent higher in 1955 and 45 per cent greater in 1965 had the shares not been established. Similarly, acreage in southern California would have been 12 to 18 per cent higher in 1955 and 10 to 15 per cent higher in 1965.

While the contract system might indicate that processing capacity should be considered in the estimation of acreage response, the analysis has failed to accord it any importance. Possibly, processors' efforts to fill their capacity have not significantly influenced farmers' decisions except through the adjustment of price.

Alfalfa response. Performance of the Nerlovian partial adjustment mechanism in the analysis of alfalfa acreage response usually gave results contrary to what prior expectations might indicate. Alfalfa hay is a perennial crop which normally produces from 3 to 5 years with one planting. Thus, one might expect the coefficients of the lagged acreage variables to be in the neighborhood of 0.67 to 0.80. In the San Joaquin and Sacramento valleys and in the Central Coast, however, the estimates of these coefficients appeared to be far lower. Perhaps, then, farmers have responded much more to prices, yields, and indirect government controls by lengthening the production period when conditions are favorable and cutting it short when conditions are unfavorable. Thus, a much greater percentage of the acreage would be entering the decision process in any given period.

In the mountain regions (at least in the equations estimated by Models 1 and 3) the coefficient of lagged acreage appears to be somewhat overestimated. Since acreage has always changed slowly from year to year, the lagged acreage variable leads to a good fit although some important structural information might be lost. The problem may well be due to the poor data available for alfalfa (see Appendix C). The alfalfa returns variable did not seem to perform at all well in the mountain regions.

Inefficiency and inequity in the government programs. Apparently, in California where so many profitable production alternatives exist, some government program costs could have been avoided without significantly altering the outcome. For example, the estimated equations indicate that all of the shift away from feed grains in the central coast, mountain regions, and northern California under the feed-grains program is essentially explained by price and yield considerations and government programs provided for other crops. In none of these districts could the feed-grain program be shown of significance for barley, which accounts for nearly 95 per cent of the districts' feed grain acreage, while participation rates ranged in the neighborhood of 30 to 40 per cent. Perhaps a good part of the small acreage diverted may have been rotated out of production anyway. Although feed grain acreages would doubtless have been somewhat higher than the observed data, as much as $392,000 in price-support payments and $581,000 in diversion payments could have been eliminated in 1970 without significantly affecting acreage response had the programs not been set up in these three districts. Accordingly, the cost of the feed-grains program would have been cut by almost 10 per cent.

Evidently, the effectiveness of the feed-grains program in terms of relative acreage reductions for corn and sorghum has been nearly the same for all of the districts where the program appears of significance. This also appears to be the case for cotton, wheat, and perhaps rice in all of the districts studied. Although the effectiveness of these programs might appear to be somewhat less in the San Joaquin Valley, this interpretation results only from the high correlation existing between the allotment variables and the allotment indicator variables. In the case of each of the three programs in the San Joaquin Valley, the respective equations indicate that much less

[62] Although shares were established in 1966, they were not restricting. Hence, the indicator variable used for sugar beet shares in the econometric analysis was equal to one only for 1955 through 1960 and 1965.

than 100 per cent of each additional allotted acre would actually be planted. However, in each case the estimated coefficients of the allotment indicator variables appear to be proportionally less than similar coefficients in other districts of the state relative to the usual district acreages.[63] For example, the reported equations indicate that only 74 per cent of an additional allotted acre of cotton would be planted in the San Joaquin Valley. Also, however, the coefficient of the cotton allotment indicator variable in the San Joaquin Valley is nearly double the usual acreage planted in the 1960's, while the coefficient for the Imperial Valley is closer to 2.5 or 3 times the normal acreages. Since the allotment variable and the indicator variable are highly correlated and the effects of the two are in opposite directions, both have apparently been underestimated in absolute value while maintaining a reasonable fit. By replacing the two variables with a single-indicator variable as in (2.24) or (2.26), it can be verified that the cotton allotment has had the same relative effect as in southern California. Similarly, the same results can be shown for San Joaquin Valley wheat with regard to all other districts in the state.

For rice, the single-allotment variable formulation indicates that allotments have actually been relatively more restrictive in the San Joaquin Valley. This implication probably stems from the shift in allotment acreage to the Sacramento Valley which took place with the imposition of restrictions (Johnston and Dean, 1969).

Evidently, the programs with strict allotments have provided an equitable arrangement for farmers in the sense that restrictions in all areas of the state have had the same relative effects on acreage.[64] Such does not appear to be the case with the proportionate shares established for sugar beets in the late 1950's and mid-1960's. In both the San Joaquin and Sacramento valleys (as stated before) results of estimation indicate that acreage reductions were due to price and yield considerations as well as to government programs affecting competing crops, and they would have occurred regardless of share imposition. In the central coast, where acreages were normally about 30,000 or 40,000, the reduction due to the shares is indicated as over 16,000 acres; while in southern California, where acreages range from 45,000 to 75,000 acres, estimated reduction due to the shares was only 6,000 to 8,000 acres. Hence, it seems that perhaps an undue burden was placed on sugar beet producers in the central coast, particularly when one considers that fewer profitable field crop production alternatives exist in that district.

Stabilizing effects of the programs. Since one of the major goals of the government programs is the stabilization of farm income, the estimated parameters θ and ϕ are of particular interest because they allow the estimation of farmers' average subjective risk both before and after the implementation of restricting programs. By employing statewide price and yield data prior to 1949 adjusted by observed variation among districts after 1949, table 8 was constructed to observe the changes in subjective mean and risk that might be associated with the programs.[65] Since table 8 includes the changes associated with yields, table 9 was also constructed and it estimates the changes associated only with prices. (The corresponding table for yield variability is given in Appendix A.) In each case, the θ_j and ϕ_j used were the ones estimated by the most general model reported in tables 2 through 7. When a ϕ_j was

[63] Cotton in the Central Coast and rice in the Mountain Region are not included in this analysis since each district produces only an insignificant amount of the respective crop. Apparently, allotments really are much less restrictive for these crops and districts, at least at the margin.

[64] Of course, the programs might still be classified as inequitable when the profitability of production alternatives in the various districts is considered.

[65] The data reported in table 8 then differ in two ways from the variables in (4.2) used in the regression analysis. First, data prior to 1949 were used since a good deal of the subjective knowledge in 1954 was indicated to be based on observations prior to 1949; and, second, total weightings in each case were inflated to unity by adjusting the weighting of the 1941–1953 period.

TABLE 9

FARMER'S SUBJECTIVE MEAN AND VARIANCE OF RETURNS BEFORE AND AFTER THE IMPLEMENTATION OF RESTRICTING PROGRAMS FOR CONSTANT NORMALIZED YIELDS

Crop and district	1954		1970	
	Mean	Variance	Mean	Variance
Barley				
San Joaquin	1.14	0.07	1.13	0.00
Sacramento	1.11	0.07	1.11	0.07
Southern	1.26	0.04	1.14	0.01
Central coast	1.13	0.07	1.12	0.02
Mountain	1.36	0.03	1.15	0.00
Northern	1.19	0.06	1.13	0.00
Cotton*				
San Joaquin	157.04	224.15	117.15	214.34
Southern	163.97	923.72	137.06	573.99
Central coast	156.17	102.02	116.45	91.86
Rice				
San Joaquin	5.38	0.74	4.80	0.12
Sacramento	5.39	0.81	4.89	0.04
Mountain	5.46	0.37	4.89	0.05
Sugar beets†				
San Joaquin	14.32	0.67	15.22	0.67
Sacramento	14.19	1.02	15.22	1.13
Southern	14.27	1.71	15.14	1.04
Central coast	14.25	1.55	15.26	1.38
Wheat				
San Joaquin	1.82	0.14	1.72	0.13
Sacramento	1.71	0.19	1.72	0.18
Southern	2.08	0.02	1.51	0.04
Central coast	2.10	0.01	1.49	0.04
Mountain	2.10	0.01	1.49	0.04
Northern	2.10	0.01	1.49	0.04
Alfalfa				
San Joaquin	21.65	93.42	28.48	6.68
Sacramento	24.60	52.31	27.88	4.75
Southern	23.37	71.88	28.11	4.94
Central coast	24.73	52.06	27.85	4.32
Mountain	23.49	26.41	23.99	23.78
Northern	24.86	39.67	27.82	32.72
Corn				
San Joaquin	1.90	0.03	1.41	0.00
Sacramento	1.86	0.04	1.42	0.01
Southern	1.89	0.03	1.41	0.00
Central coast	1.90	0.02	1.40	0.00
Mountain	1.89	0.03	1.45	0.00
Grain sorghum				
San Joaquin	1.65	0.04	1.25	0.00
Sacramento	1.65	0.04	1.25	0.00
Southern	1.62	0.04	1.25	0.02
Central coast	1.50	0.06	1.32	0.05
Mountain	1.61	0.04	1.25	0.00

*Excludes cottonseed.

†Includes Government payments to producers.

not estimated, it was taken as $1 - \theta_j$. For those equations in which neither was estimated, the average of points plotted in figure 20 was used.

Results seem to indicate that feed grains and rice programs have been quite successful in achieving stability. Reductions in subjective variance are substantial in most districts for these crops. For barley, however, much of the reduction in subjective variance occurred shortly after the imposition of quotas on cotton, rice, and wheat in 1954 and 1955. Only the stabilization of corn and sorghum prices seems to be directly attributable to the establishment of feed-grains program. Since stabilizing effects are sizable, results suggest that voluntary programs have actually led to much smaller acreage reductions than participation coefficients indicate. In determining the effects of the programs, expansionary effects of stabilization, as well as restricting effects of participation, must be included if an accurate evaluation is to be made. Hence, the preceding calculations relating to the effectiveness of the programs must be examined with caution since they ignore the direct effect that government programs may have on risk. Although the reductions in risk that can actually be attributed to the programs are not estimated in the present study, results of Models 2 and 3 indicate that the effect of total risk reduction has more than offset the restricting effects of the feed-grains program in the case of grain sorghum. While subjective risk has also fallen rapidly for corn, similar results are not found in that case as risk has apparently been of less importance in corn acreage decisions.

Subjective variances associated with price instability have not fallen nearly so dramatically for cotton, and subjective means have more than offset the reduction in variance if a measure such as the subjective coefficient of variation is used. For both wheat and sugar beets, risk has apparently increased. The high subjective risk for wheat is apparently a carryover from the abolition of national marketing quotas in 1964. Prices dropped dramatically as a result of substantial increase in national production, but prices have continued to be unstable since. Interestingly, the sugar beet price series unadjusted by government payments to producers indicates a much lower subjective variance of returns (on the order of one-fourth to one-half of that reported in table 9) and almost no increase in variance for at least three districts. The government payment series has apparently been much more variable because it includes abandonment and deficiency payments made in bad crop years. The effects of the sugar beet program in stabilizing farm income should then be more adequately evaluated in table 8 rather than table 9. According to table 8, the subjective variance associated with sugar beet production has increased substantially in some cases and has not fallen in any case.

For alfalfa, as for barley, stabilization of prices seems to have occurred as a result of the establishment of stabilizing programs for competing crops. Perhaps some of the stability in alfalfa prices has resulted from the efforts of alfalfa marketing cooperatives, but in most districts the reduction in estimated subjective variance occurs gradually in a 3-to-5-year period following the imposition of marketing quotas for cotton, rice, and wheat in 1954 and 1955. Perhaps, increased alfalfa acreages are then attributable to both the stabilizing and restricting effects of allotment programs for other crops.

Appraisal of the government program model. The government program component of the model seems to have given reasonable results in almost every case for allotment and price-support variables. For crops where CCC acquisitions have been negligible and production has not been controlled by voluntary allotments, price-support levels could not be shown to be of significance; furthermore, in many cases reasonable results could not be obtained without their inclusion for crops where acquisitions have been substantial. For crops controlled by voluntary allotments, price supports

were sometimes important even when CCC acquisitions were negligible because sizable direct support payments were made to compliers.

Allotment variables also performed well for the crops controlled by strict allotments. In some cases, almost all acreage variation appears to be due to allotments and (perhaps) price-support levels. Although some problems were encountered with the two allotment variable formulations due to high correlation of the two variables, reduction to one allotment variable, as indicated in (2.24) or (2.26), was effective in alleviating such difficulties. Indeed, this simplification of the model is designed for application in exactly the circumstances where the correlation of the two variables is high, i.e., when allotments have been changing little.

Unfortunately, however, the diversion variables did not often appear significant although *a priori* considerations indicated they should. At least for the feed grains and wheat programs, however, the effect of diverted acreage is probably carried in the allotment participation variables since minimum and maximum diversion restrictions placed on complying farms resulted in highly correlated participation and diversion variables. Coefficients of participation should probably then be interpreted according to (2.21) since they might carry the effects of diversion in addition to the effects of participation. The same might also be said of the price-support variables since, in each case, they include the participation variables as factors; but (as shown in Appendix D) price-support variables may be of greater significance than indicated in tables 2-7 if their relationships with the participation variables are considered. Apparently, the organization of past programs is responsible for preventing the econometric isolation of the effects of participation and diversion, and perhaps a better approach in this case might have been to restrict the coefficient of diversion in some way on theoretical grounds.

Other directions in future work might also involve simultaneous estimation methods in which constraints on the total effect of programs could be imposed. For example, if total acreage were nearly constant, any acreage reduction caused by a simple allotment without diversion requirements should be matched by acreage expansions for the competing crops. In this framework the acreage required to be devoted to conserving uses under some of the programs could then also be brought into the model. In this study conserving base acreage has been ignored since it is of small magnitude relative to the total field crop acreage, and because the constraint is imposed on total acreage rather than on the acreage of any particular crop.

Appraisal of Alternative Estimation Models and Concluding Remarks

In general, performance of the model in (4.2) in the analysis of California field crop acreage response may be classified as quite good. Results are most encouraging for crops and districts in which production is large. Well over 90 per cent of the acreage variation in the San Joaquin Valley, the most important district, is explained when risk variables are included in the analysis. The poorest results are generally obtained for crops that are least important in the district in question. The somewhat poor fit obtained for alfalfa equations might also be attributed to errors in data as quite a large percentage of the data came from relatively unreliable sources (Appendix C).

In many cases, however, particularly those for which government programs are less important, the standard multivariate Nerlovian Model (corresponding to Model 1) fails to capture adequately one of the most important forces operative in acreage response. The more general models have often indicated risk to be quite significant in acreage response particularly when the results of Appendix D are considered.

In some cases only Models 2 and 3, which include risk, gave any reasonable results (Appendix B). In general, equations in which risk did not appear significant pertained to crops strongly regulated by government programs. Hence, the results suggested that hypothesis (a), as pertaining to all field crops, should be rejected.

Perhaps even more general implications might be drawn from the results. In point of fact, the widely used Nerlovian model

$$d_t = A_o + A_1\left[\theta \sum_{k=0}^{\infty} (1-\theta)^k s_{t-k-1}\right] + \varepsilon_t$$

has been commonly estimated in its reduced form,

$$d_t = (1-\theta)\, d_{t-1} + \theta A_o + \theta A_1 s_{t-1} + v_t \tag{4.3}$$

where

$$v_t = \varepsilon_t - (1-\theta)\varepsilon_{t-1}.$$

In the adaptive expectations context, the term $(1-\theta)\, d_{t-1}$ is then thought to carry only information relating to the subjective mean of the distribution of s_t. However, if Models 2 or 3 are actually operative, that term may carry far more information. Consider the corresponding case under Model 3 where $\phi = 1 - \theta$ and

$$d_t = A_o + A_1\left[\theta \sum_{k=0}^{\infty} (1-\theta)^k s_{t-k-1}\right] + A_2\left\{\theta \sum_{k=1}^{\infty} (1-\theta)^k\left[s_{t-k-1} - \theta \sum_{j=0}^{\infty} (1-\theta)^j s_{t-k-j-2}\right]^2\right\} + \varepsilon_t.$$

Similarly, the reduced form would be found as

$$d_t = (1-\theta)\, d_{t-1} + \theta A_o + \theta A_1 s_{t-1} + \theta A_2\left[s_{t-1} - \theta \sum_{j=0}^{\infty} (1-\theta)^j s_{t-j-2}\right]^2 + v_t. \tag{4.4}$$

Now the term $(1-\theta)\, d_{t-1}$ additionally carries some of the effects of the variation in subjective risk. Moreover, when θ is close to zero, as it seems to be in many cases in this study, almost all effects of changing subjective risk may enter through the term $(1-\theta)\, d_{t-1}$. Hence, one might be able to obtain results that appear to be quite satisfactory using the standard Nerlovian model when, in actuality, much of the real explanation is lost with the exclusion of risk.

Furthermore, tests based on the Durbin-Watson statistic or spectral analysis might lead one to erroneously conclude that the partial adjustment model is operative when in fact the adaptive expectations mechanism is of importance. As is evident from (4.3), when the term

$$A_2\left[s_{t-1} - \theta \sum_{j=0}^{\infty} (1-\theta)^j s_{t-j-2}\right]^2$$

is not highly correlated with other variables in the model, the estimated disturbances would actually be estimating

$$\begin{aligned} \underline{v}_t &= \theta A_2\left[s_{t-1} - \theta \sum_{j=0}^{\infty} (1-\theta)^j s_{t-j-2}\right]^2 + v_t - c_{\underline{v}} \\ &= \theta A_2\left[s_{t-1} - \theta \sum_{j=0}^{\infty} (1-\theta)^j s_{t-j-1}\right]^2 + \varepsilon_t - (1-\theta)\varepsilon_{t-1} - c_{\underline{v}} \end{aligned}$$

if the Nerlovian model were used when risk is actually important (where $c_{\underline{v}}$ is the expected value of the first term during the period of estimation). If the variation in

the first term dominates that of v_t, then the disturbance process could more closely resemble white noise. As is well known, the theoretical disturbance process in a Nerlovian partial adjustment model is white noise while in an adaptive expectations model the disturbances are $v_t = \varepsilon_t - (1 - \theta)\varepsilon_{t-1}$ where the $\{\varepsilon_t\}$ process is white noise. As is demonstrated in Appendix E, the v_t process does not resemble white noise when $(1 - \theta)$ is not close to zero.

In this study the Nerlovian model (Model 1), as well as the more general models, has been estimated in its structural form to prevent the possible biased performance of lagged acreage variables when such low-frequency variables as risk are excluded. As shown in Appendix E, the low-frequency noise indicated by the Nerlovian formulation is significant for many of the California field crops. But much of the disproportionate dominance by low-frequency noise also seems to disappear when risk terms are added to the explanatory model. This low-frequency variation thus appears to be exactly the kind of variation which would be incorrectly explained with a lagged dependent variable if the reduced form of the Nerlovian model were estimated.

Conclusions

Although the presence of some of the government programs has prevented the simplified estimation of complete reduced form equations such as (4.3) and (4.4), some preliminary results have indicated in cases where risk is apparently important that (1) good fit is often obtained with the reduced form of the standard Nerlovian model, (2) fit usually deteriorates when the structural form of the Nerlovian model is estimated, and (3) fit once again improves when risk variables are added to the structural form. These results then cast doubt or at least should lead us to exercise caution in interpreting and using the large number of studies which make use of the standard Nerlovian model in an adaptive expectations context.

Some may argue that a Nerlovian approach might still be useful for predictive purposes, but this would only be the case when the level of subjective risk relative to the level of the subjective mean is nearly constant. Such an assumption should not be imposed *ad hoc* in the evaluation of government programs. If stabilization is to be achieved by a program, then the possibility of predicting changes in response induced by reduction in risk would be completely lost. Thus, the correct evaluation of the programs and the estimation of the effects of attaining the goals of policy would also be impossible.

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