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RETURNS TO PUBLIC AGRICULTURAL RESEARCH EXPENDITURE
UNDER UNCERTAINTY

by

Sanjeev Misra

A thesis submitted in partial fulfillment
of the requirements for the degree

of

MASTER OF SCIENCE

in

Economics

Approved:



UTAH STATE UNIVERSITY
Logan, Utah

2000

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ABSTRACT

Returns to Public Agricultural Expenditure
Under Uncertainty

by

Sanjeev Misra, Master of Science

Utah State University, 2000

Major Professor: Dr. Christopher Fawson
Department: Economics

A vast literature has investigated the returns to investment in agriculture research and generally found extremely high rates of return. These results suggest policymakers would do well to maintain or increase resource allocation to public agricultural research. Remarkably little attention has been paid, however, to the issue of how best to allocate public agricultural research funding between competing research areas and organizations. This paper considers the relative returns to alternative uses of public agricultural research funds committed to the agricultural experiment stations of 10 western states of the United States over the years 1967-91. A model of expected utility maximization subject to risk is presented with comparative analysis. After establishing empirically that the mean variance analysis would be an inappropriate method to solving the problem, a stochastic dominance testing method is employed to identify dominated and undominated research categories and state agricultural experiment stations. The mean variance analysis also is used to evaluate

whether research productivity has been increasing or decreasing over time, and to establish which among the western states hold absolute advantage in particular research areas.

(101 pages)

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Sanjeev Misra

CONTENTS

	Page
ABSTRACT	iii
ACKNOWLEDGMENTS	v
LIST OF TABLES	vii
LIST OF FIGURES	x
CHAPTER	
1. INTRODUCTION	1
2. ECONOMICS OF RESEARCH	6
3. EXPECTED UTILITY: A DIGRESSION	13
4. CONSISTENT TWO-MOMENT MODELS OF EXPECTED UTILITY	22
5. THE MODEL AND SOME COMPARATIVE STATIC IMPLICATIONS	27
6. STOCHASTIC DOMINANCE AND ITS APPLICABILITY	38
7. THE DATA, APPLICATION OF STOCHASTIC DOMINANCE, AND TEST RESULTS	42
8. CONCLUSIONS	49
REFERENCES	50
APPENDICES	53
Appendix A: Mathematical Derivations	54
Appendix B: Detailed Results	61
Appendix C: Data	88

LIST OF TABLES

Table	Page
1. UNCONDITIONAL STOCHASTIC DOMINANCE TESTING RESULTS	45 46
2. RESEARCH AREA EFFICIENCY SETS BY STATE	44 47
3. SAES ABSOLUTE ADVANTAGE RANKINGS	48
B.1. ALL-STATE COMPARISON OF 19 PROGRAM CATEGORIES AND 23 YEARS . .	69
B.2. AGGREGATION OF THE 10 STATES (YEARS NATIONAL)	69
B.3. CATEGORIES AGGREGATED ACROSS ALL STATES (PROGRAM CATEGORIES— NATIONAL)	70
B.4. PROGRAM CATEGORIES—ARIZONA	70
B.5. PROGRAM CATEGORIES—CALIFORNIA	71
B.6. PROGRAM CATEGORIES—COLORADO	71
B.7. PROGRAM CATEGORIES—IDAHO	72
B.8. PROGRAM CATEGORIES—KANSAS	72
B.9. PROGRAM CATEGORIES—MONTANA	73
B.10. PROGRAM CATEGORIES—NEW MEXICO	73
B.11. PROGRAM CATEGORIES—NEVADA	74
B.12. PROGRAM CATEGORIES—OREGON	74
B.13. PROGRAM CATEGORIES—UTAH	75
B.14. MOST PRODUCTIVE YEARS PER RESEARCH DOLLAR SPENT—ARIZONA . .	75
B.15. MOST PRODUCTIVE YEARS PER RESEARCH DOLLAR SPENT—CALIFORNIA	76
B.16. MOST PRODUCTIVE YEARS PER RESEARCH DOLLAR SPENT—COLORADO	76

B.17.	MOST PRODUCTIVE YEARS PER RESEARCH DOLLAR SPENT—IDAHO	77
B.18.	MOST PRODUCTIVE YEARS PER RESEARCH DOLLAR SPENT—KANSAS . . .	77
B.19.	MOST PRODUCTIVE YEARS PER RESEARCH DOLLAR SPENT—MONTANA .	78
B.20.	MOST PRODUCTIVE YEARS PER RESEARCH DOLLAR SPENT—NEW MEXICO	78
B.21.	MOST PRODUCTIVE YEARS PER RESEARCH DOLLAR SPENT—NEVADA . .	79
B.22.	MOST PRODUCTIVE YEARS PER RESEARCH DOLLAR SPENT—OREGON . . .	79
B.23.	MOST PRODUCTIVE YEARS PER RESEARCH DOLLAR SPENT—UTAH	80
B.24.	MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM CATEGORY 1—FEED GRAINS	80
B.25.	MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM CATEGORY 2—FOOD GRAINS	81
B.26.	MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM CATEGORY 3—OIL CROPS	81
B.27.	MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM CATEGORY 4—FRUITS & NUTS	81
B.28.	MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM CATEGORY 5—VEGETABLES	82
B.29.	MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM CATEGORY 7—TOBACCO	82
B.30.	MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM CATEGORY 8—MEAT ANIMAL, MISCELLANEOUS LIVESTOCK, AND FISH	82
B.31.	MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM CATEGORY 9—DAIRY PRODUCTS	83
B.32.	MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM CATEGORY 10—POULTRY	83

B.33.	MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM CATEGORY 11—OTHER CROPS	83
B.34.	MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM CATEGORY 12—FOREST & FOREST PRODUCTS	84
B.35.	MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM CATEGORY 13—SOIL, WATER, AIR, & CLIMATE	84
B.36.	MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM CATEGORY 14—RECREATION	85
B.37.	MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM CATEGORY 15—TECHNOLOGY OF PRODUCTION	85
B.38.	MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM CATEGORY 16—AGRICULTURE IN SOCIETY	86
B.39.	MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM CATEGORY 17—AGRICULTURE ENTERPRISE	86
B.40.	MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM CATEGORY 18—WEEDS, SEEDS, & BUGS	87
B.41.	MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM CATEGORY 19—BASIC RESEARCH	87

LIST OF FIGURES

Figure	Page
1. Indifference curve properties of a quadratic utility function represented in mean, standard deviation space	18
2. Quadratic utility and its implied increasing marginal rate of substitution for constant risk	20
3. Optimal research portfolio choice given the decision makers preference structure	33

CHAPTER 1

INTRODUCTION

The literature on public agricultural research for the last two decades has been dominated by the funding structure of the same. Among the issues that have filtered out of such discussions, an important one is that of the productivity implications of public agricultural research. It has been well documented over the years that the benefits accrued from public agricultural research, due to improved variety of crops, improved production technology, etc., are much more than the cost associated with the research process. The issues that still remain are the methods of funding, namely, formula funding vs. competitive grants, where both have their pros and cons (for a detailed paper see Norton et al. 1995). The other issue that is being quite extensively debated is the decline of total real state agricultural experiment station (SAES) funds over time. However, remarkably little attention has been paid to the issue of how best to allocate public agricultural experiment research funding between competing research areas and organizations. This paper considers the relative returns to alternative uses of public agricultural funds committed to the agricultural experiment stations of the 10 western states in the United States over the years 1967-91.

Arguments for and against formula and competitive grant distribution of federal funds for SAES have been made for many years. Even though most economists associated with the SAES give convincing arguments in favor of formula funding as being more productive, the federal disbursement of funds to the states has been tending more towards the competitive grant system. Some people have argued that formula funded

research has weak ties to science and produces too many duplicative projects. But, as the outcome of any research project is uncertain, it is generally in society's interest to hold a portfolio of active projects on any scientific or technological problem worth pursuing. That is, parallelism need not imply waste unless, of course, increasing returns to scale outweigh the benefits from diversification, in which case it would be desirable to pursue only one project.

On the other hand, competitive grants are believed to foster both enhanced quality and quantity of research production due to competition for receiving funds. However, there has been a growing body of literature that cautions about the low productivity of competitive grant funding relative to formula funding of public agricultural research. The arguments it places are that a lot of productive scientist hours are utilized, without any productive offshoot, on proposal preparation, which could be used for other productive activities, and, moreover, transaction costs are much higher in the case of competitive funding. A recent study by Norton et al. (1995) states that two and a half scientist months were spent in 1994 on proposal preparation per successful competitive grant proposal. Huffman and Just (1994) empirically evaluated the productivity from different sources of funds for agricultural research and concluded that "the current trend towards competitive grants and earmarked funding, as opposed to formula funding from federal sources, apparently reduces productivity of research expenditures" (p. 145).

Unfortunately, the questions about the trend towards competitive grants funding have attracted little attention. The U.S. Office of Management and Budget, the U.S. Congress, and other decision makers have determined that competitive grants funding, rather than

being a supplement to foster priority agricultural research, will be a substitute for the formula funding. This imposes an unwelcome restriction on the historically productive national agricultural research effort.

Due to the controversy between competitive grants funding and formula funding of public agricultural research and imminent budget cuts, U.S. public agricultural research in the 1990s has been struggling to fulfill the ever-growing need for innovation with very scarce resources. Such conditions have led to more stringent controls over research projects. Moreover, as the extension and research problems of agriculture and rural areas have expanded beyond traditional agricultural interests, the administrative structure of many SAESs is changing. Hence, the stations are geared more towards increasing the returns to public agricultural research expenditure by increasing the quality and quantity of output, that is, production of new technology or knowledge that is in concordance with the station's broad research objectives.

To look at the returns to public agricultural research expenditures, that is, the productivity of the research-producing institution, one needs to comprehend the maximizing behavior of the research-producing agent. The benefits from public agricultural research do not accrue to the research scientist per se, but to research output users, that is, to the farmers as producers' surplus, consumers as consumers' surplus, and to resource owners as rents. The consequence of this peculiar characteristic of public agricultural research surfaces in the maximizing behavior of the research-producing agent. This paper focuses on this very problem.

Chapter 6 empirically specifies the problem at hand using stochastic dominance.

Chapter 7 describes the data and application of stochastic dominance to it, and discusses the results, and chapter 8 presents the conclusions.

CHAPTER 2

ECONOMICS OF RESEARCH

The objective of an experiment station is to ensure the greatest expected return for the research money spent at the experiment station. The primary function of the station is to produce new, agriculturally oriented knowledge through scientific inquiry. The need to add to the existing stock of this kind of knowledge is almost unlimited. But, with limited resources, choices among research activities have to be made. If all research expenditures are not of equal value, then careful selection, based on a systematic analysis of alternatives and their likely consequences, should allow the station to develop a more valuable research program.

One of the primary goals of the research produced by a SAES is to relax constraints on production through use of new inputs or practices that substitute relatively abundant resources for relatively scarce ones. Research, therefore, is a form of agricultural investment. Research has dynamic effects; costs incurred today can produce innovation that allows increased agricultural output at lower average cost in the future. The benefits last for many years, until more efficient ones replace the innovations. If new knowledge is viewed as an instrument, it follows that the social benefits of research consist of the contributions to social goal attainment. For example, social goals concerned with public agricultural research could be pushing the frontier of food production, keeping in mind particularly the issues of environmental pollution, food safety, nutrition, etc. The benefits from research are represented by the stream of increments to social goal levels that are attributable to the output of new knowledge.

Knowledge can be perceived as a form of social capital, and research expenditure is a form of social investment that increases the stock of knowledge capital. New knowledge can produce a sustained increase in goal levels over time in much the same way that conventional investment produces a sustained increase in income. Thus the benefits from research over time constitute a sustained stream or flow of values that are subject to the usual discounting process.

The SAES, which receives a fixed research budget every financial year to produce a sustained stream of knowledge, must allocate that budget among different departments and, consequently, among different research projects within the department. The primary sources of funds available to SAES have been federal funds appropriated on a formula basis and funds appropriated for agricultural research by state governments.

The appropriation of funds for agricultural research by SAES is a very interesting process. As market forces do not set the price of the research directly, the amount of money that the SAES receives is more due to the political-economic influence at the state legislature and the congress. The use of the voting mechanism to decide the amount of funds to be allocated to research can be regarded as a highly imperfect allocative process, for it is subject to the vagaries of politics and judgments of inadequately informed voters.

Once the SAES gets the funds for research expenditure for a fiscal year, and given the forces influencing the environment in which administrators and research workers in the agricultural experiment stations make decisions regarding the use of research funds, the existing research planning and decision-making structure in most of the experiment

stations is organized as follows. The station director is responsible for the allocation of funds or the distribution of funds among the research departments of the institution and research personnel for competing areas of work. The project leader is responsible for the allocation of funds among the competing problem areas.

Given the funds for research, the research output depends on the prices of research inputs and on the state of the research art. The prices of the research inputs are determined in competitive markets and they are for all practical purposes readily available. Substitution and complementary considerations in combining different scientists and facilities and the optimum scale of the research enterprise depend on the research art. The state of the art is the essence of the problem of trying to specify the research possibilities and, hence, the supply of new information available from research. So it boils down to a matter of rating the research possibilities of alternate projects.

Research is not a homogeneous activity. It involves many scientific disciplines and many subject areas. Since these combined or solo contributions may vary widely among alternative research activities, some kind of research may be more valuable than others. Therefore, a reorganization of the mix of research activities may influence the social return from public research investment. Even though a large number of pure research or inventive activity has been uneconomic, the rates of return on the successful ones are sufficiently large to cover the costs of unsuccessful operations. Hence, the skewed distribution towards unsuccessful research should not be regarded as a waste, as the ex ante seeding of successful projects from the unsuccessful ones cannot be done. Hence, it is in society's interest to hold a portfolio of research.

The question of consequence is what portfolio of research to hold or what are the problem areas to concentrate research on. If we think of the SAES scientist as one who maximizes his/her own utility by maximizing the research output, then by doing this he/she consequently maximizes the station's utility. I assume that the researchers and the SAES utility are monotonically increasing in research publication, which implies maximizing expected publications. In order to do this and receive grants for projects, he/she should be responsive to the demand for any specific research output. Even though there is a missing market for public agricultural research, where the demander of research does not pay the supplier of the same (SAES) directly, the demand for public agricultural research can be fathomed to some extent if not in a precise mathematical sense.

Although public agricultural research products are a public good, region-specific demanders cannot expect to borrow all their research products from other states. Research output as a form of information is a nonexcludable public good and use of it by one agent does not reduce the quantity available to others. However, the benefits to users may vary, but for social efficiency such information should be made available to all potential users at the marginal cost of distribution. Even though the knowledge produced by one experiment station can be borrowed by another, the potential for extensive interstate borrowing of applied research product is usually restricted due to the regional specificity of the information produced. Under these conditions a state demand function for indigenously produced applied research exists. This demand is hypothesized to be a function of the size and other characteristics of the agricultural

output, input prices, farmers' education, extension, the price of indigenous applied research, and agricultural research in other competing states. Huffman and Evenson (1993) hypothesized that as applied research is location specific, any increment in knowledge that increases the agricultural output puts farmers in other states at a comparative disadvantage unless new research products are developed for them. Hence, nonborrowable research output in competing states can be expected to shift rightward the demand for indigenous applied research.

To satisfy this demand, or at least in an endeavor to do the same, the research product in this paper is supplied by the state experiment stations. The production of research requires, as inputs, the service of administrators, research scientists, research assistants, as well as the infrastructure necessary for research production. We assume that the experiment station produces research at a minimum average cost where marginal cost equals average cost. The supply or the cost function of indigenous agricultural research is hypothesized to be a function of prices of the inputs, of quantity of research output, and factors exogenous to resources allocation decisions like the entrepreneurial capabilities of the station director. Research is a creative activity where ideas must be combined so that something "new" is produced. As research requires sustained effort, the productivity of research time is likely to be low if individuals are continually being disrupted by nonresearch activities or if their working hours are primarily allocated to nonresearch activities, such as teaching, because this leaves less time for research. It also may be so that researchers may not have good enough ideas and hence the productivity is low, even when most of their time is devoted to research.

As evident from the above discussion, the deterministic economic calculus of conventional firm theory is difficult to apply *ex ante*, especially to production of research. The production function relating research input to research output is stochastic in nature and unknown before the output is realized, and inputs such as creative minds necessary for the production process cannot be identified or produced in a very predictable manner. Since the conventional production function approach is not applicable, it is necessary to incorporate the probabilistic characteristics of research projects into the production function in analyzing the relationships between research inputs and outputs (Schultz 1971).

Due to the stochastic nature of the production process of knowledge or new technology, the problem needs to be cast in a probabilistic sense and can be addressed in an expected utility framework. In this paper the decision maker(s) (i.e., station director, department heads, and research scientists or project leader) can be thought of as a scientist who utilizes all his/her information to maximize the benefits that personally accrue to him/her. With successful completion of a project, the research scientists or the research director gains both pecuniary as well as nonpecuniary rewards. Examples would be monetary perquisites for successful completion of a project, academic recognition, professional achievement, etc. Hence it can be thought of as his/her personal utility level has a linear dependence on the number of successful projects during the financial year. Thus, the benefits that accrue personally to the research producers are a function of the research output. In an effort to maximize his/her personal utility, he/she tries to maximize the research (knowledge) output, which is in the form of published

papers and reports. Therefore to maximize the returns to public agricultural research expenditure, that is, to maximize the research output, the behavioral principle of this agent can be represented in an expected utility framework, where utility is defined over the real line and is a function of published papers and reports funded by the SAES.

CHAPTER 3

EXPECTED UTILITY: A DIGRESSION

In numerous situations, the SAES director/scientist(s) (called the decision maker hereafter), is fully aware of the fact that he/she is operating under conditions of incomplete information. Moreover, in many such situations, he/she may be able to characterize the state of uncertainty in quantitative terms by making probability statements about the outcomes of alternative research effort. What is essential in this kind of situation is that, while each action taken by the decision maker will eventually yield one particular level of outcome, he/she does not know in advance exactly what the level of realized research output will be. I do assume, however, that the decision maker can attach subjective probabilities to all possible levels of output. Each action is, therefore, associated with various levels of output and their respective probabilities, and so, when a decision maker decides on a particular action, he/she is really choosing a particular probability distribution.

Given a fixed budget for research, the decision maker, that is, the department head has to choose among the different alternative competing research projects and must allocate the budget among the ones he/she chooses to undertake. He/she must allocate the funds in such a way that he/she maximizes his/her objective function. Now, if the decision maker's objective is to maximize the expected utility, then we can think of a general bundle of outcomes as having research output levels of $Y_1, Y_2, Y_3, \dots, Y_n$, that is, different possible levels of output of each research venture funded by SAES, with associated

probabilities $\alpha_1, \alpha_2, \alpha_3, \dots, \alpha_n$, then the expected utility from published papers can be written as

$$\sum_{i=1}^n \alpha_i u(Y_i) = E[u(Y_1, Y_2, Y_3, \dots, Y_n; \alpha_1, \alpha_2, \alpha_3, \dots, \alpha_n)], \quad (1)$$

where $u(Y_i)$ is an ordinary utility function and $E[u(\dots)]$ is the expected utility.

Although expected utility has been in existence for the last two and half centuries, as first formulated by Bernoulli (1738), it came to be widely used since its axiomatic foundation by Von Neumann and Morgenstern (1944). Even though it has found extensive use in economics of uncertainty, as a theoretical construct, its applicability as such has been limited in empirical analysis due to the subjective nature of the utility function. In most real-life experiences it becomes extremely difficult for economists to find a functional form of the individual's (or group's) utility functions to evaluate the maximizing conditions. This subjective nature of expected utility has been the prime force for development of a criterion, which should be analogous to the expected utility index and positive in nature, so it could be empirically applicable. Moreover, the expected utility derives the decision maker's attitude towards risk, but does not strive to measure the riskiness of a given situation per se. Among the varied approaches to represent expected utility, the most common method is the one where expected utility is expressed in terms of moments of the distribution of the uncertain outcome.

I. Expected Utility and the Moments of a Distribution

As assumed earlier, the decision maker can attach subjective probabilities to all

possible levels of research output. So while deciding on a particular course of action, he/she really is choosing a particular probability distribution. Probability distributions are often characterized by a set of statistics that embody a great deal of descriptive content; these are the moments of the distribution. The expected utility of any uncertain outcome can be expressed in terms of the moments of the outcome, thus giving us an alternative formulation of the expected utility function.

If we expand the utility function $u(Y)$ around mean of Y (i.e., μ), using Taylor's series expansion, the expansion takes the form,³

$$u(\mu(Y)) = u(\mu) + u'(\mu)h + \frac{u''(\mu)h^2}{2!} + \frac{u'''(\mu)h^3}{3!} + \dots + R_n, \quad (2)$$

where μ is the mean of Y and R_n is the remainder term. Applying the expectation operator to both sides of equation (2) yields

$$EU(Y) = u(\mu) + \frac{u''(\mu)m^2}{2!} + \frac{u'''(\mu)m^3}{3!} + \dots + ER_n \quad (3)$$

where m^i denotes the i th central moment, so m^1 would be the mean, m^2 the variance and m^3 the measure of skewness of the distribution. From equation (3) we can see that expected utility is the weighted sum of all the moments of the probability distribution, the weights being the derivatives of the utility function. As h is less than one, the above series is convergent. Due to this convergence, the remainder term R_n can be ignored. More often than not the expected utility is expressed as a function of the first few

³A maclaurin series can also be used for the expansion, where we can expand around the point $Y=0$.

moments of the distribution, unless the utility function is a k th degree polynomial.⁴ The first moment is the mean, which intuitively represents profitability level. The second moment, the variance, measures the dispersion and serves as a proxy for the level of risk. The third moment represents asymmetry, that is, skewness, where positive skewness is desirable in this context. The intuitive economic appeal of the first few moments has led many researchers to focus more on parametric representation of expected utility. Among the class of parametric representation of expected utility, the one that has gained immense momentum as an economic tool for portfolio analysis is the mean/variance approach. The mean/variance, or alternatively called the μ and σ criterion, where μ is the mean and σ is the standard deviation, has been widely used in the literature. As in this paper, we will be dealing with portfolios of research, it would be prudent to review the circumstances in which the mean variance approach makes sense and the non-applicability of this approach.

II. Mean/Variance Expected Utility Function

Since its inception in 1906, economic probability distribution has been evaluated by means of mean (μ) and variance (σ^2). This approach has been used and discussed extensively by Hicks (1934), whose work was reviewed and refined by Marschak (1938), Steindl (1941), and Tintner (1941). But after its application to the portfolio problem by Markowitz (1952) and later extended by Tobin (1958), the (μ, σ) criterion became the most frequently used two-parameter approach. In this approach it is assumed that a large

⁴If the utility function is a polynomial of degree two, i.e., a quadratic utility function then the $EU(Y)$ is determined by the first two terms of equation (3) only, as the rest of the terms goes to zero. So only mean μ and σ^2 characterize the probability distribution associated with a quadratic utility function.

mean or expected value of an uncertain outcome is preferred to a smaller one, and a smaller variance is preferred to a larger variance. The most common risk measure is the variance σ^2 or the standard deviation σ of a distribution with mean μ . A rational decision maker is expected to maximize μ and to minimize σ^2 in selecting the most desirable risky alternative.

In a Markowitzian sense the assumptions important for the validity of a mean-variance approach are that the utility of a probability distribution can be expressed as a function of mean and standard deviation (or variance) if (a) the utility function is quadratic, and/or (b) the probability distribution is normal. If in fact the expected utility is quadratic, then in equation (3), the moments higher than two become zero, and hence expected utility can be expressed as a function of μ and σ^2 , where μ and σ^2 are the mean and variance of Y , respectively. Formally the utility function can be expressed as

$$u(Y) = Y - \omega Y^2. \quad (4)$$

Taking the expectation of both sides of equation (4), we get

$$E[u(Y)] = E(Y) - \omega E(Y^2). \quad (5)$$

Since,

$$\sigma^2(Y) = E(Y^2) - E^2(Y),^5 \quad (6)$$

substituting the value of $\sigma^2(Y)$ in equation (5), we get

$$E[u(Y)] = E(Y) - \omega E^2(Y) - \omega \sigma^2(Y). \quad (7)$$

This can be alternatively written as

⁵ $\sigma^2(Y) = E\{[Y - E(Y)]^2\}$
 $= E[Y^2 - 2YE(Y) + E^2(Y)] = E(Y^2) - 2E(Y)E(Y) + E^2(Y) = E(Y^2) - E^2(Y)$.

$$\begin{aligned}
 E[u(Y)] &= \mu - \omega\mu^2 - \omega\sigma^2 \\
 &\equiv u(\mu, \sigma)
 \end{aligned}
 \tag{8}$$

Hence, any quadratic utility function can be expressed as a function of its mean and variance. But the problem arises when we look at the shape of the indifference curves in (μ, σ) space. The shape of the indifference curves follows directly from equation (8), thus we get concentric circles that are centered at $(0, 1/2\omega)$.⁶

Figure 1 visually illustrates the concept, showing the utility and the indifference curves in (μ, σ) space. It not only illustrates the concentric indifference curves, but also gives evidence about the nonexistence of a maximum for the utility function.

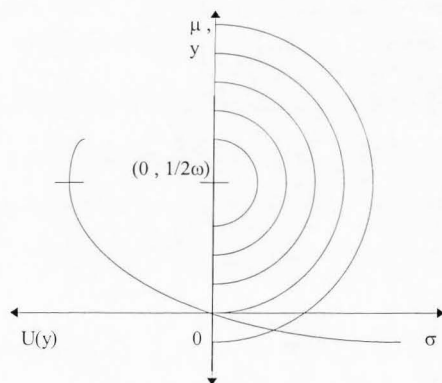


FIG. 1.—Indifference curve properties of a quadratic utility function represented in mean, standard deviation space.

⁶For the proof that the indifference curves are concentric circles, see appendix A.

The conditions just derived weaken the arguments of a (μ, σ) criterion, since a negative marginal utility is unrealistic. So, the only plausible range on the indifference curve is the range where $d\mu/d\sigma$ is greater than zero, that is, the positive sloping part of the indifference curve, which represents positive marginal utility. So given the assumption of a quadratic utility function, the mean-variance approach holds only if

$$\left. \frac{d\mu(Y)}{d\sigma(Y)} \right|_{E(u)=const.} > 0. \quad (8)$$

Even if the restriction presented by equation (9) is accepted, which limits the indifference curve to have a positive locus, there are other problems associated with the quadratic utility functions. A quadratic utility, as argued by Hicks (1933), Arrow (1951), and others, is inappropriate because it exhibits an increasing absolute risk aversion. That is, with an increase in wealth, his/her aversion to a small gamble also increases, which seems very implausible.⁷ This basically suggests that its marginal rate of substitution between expected value (μ) of the outcome and risk, as measured by σ , increases with μ for a given level of risk (σ), as shown in figure 2. So not only does equation (9) have to hold (i.e., $d\mu/d\sigma > 0$), but it has to be supplemented by the fact that

$$\left. \frac{d^2\mu(Y)}{d\sigma^2(Y)} \right|_{E(u)=const.} > 0, \quad (10)$$

which imposes a further restriction on the quadratic utility function by restricting the indifference curves to have an increasing slope.

⁷The more appropriate would be the DARA (decreasing absolute risk aversion) or CARA (constant absolute risk aversion) class of utility function. In this class a small gamble becomes more attractive as wealth increases.

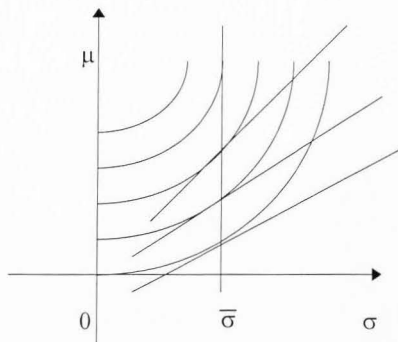


FIG. 2.—Quadratic utility and its implied increasing marginal rate of substitution for constant risk.

In addition to quadratic utility the assumption of normality in the distribution of outcomes also poses a problem. As in almost all empirical studies it was found that the distributions of the outcome hardly ever follow normality. Furthermore, Chipman (1973) shows that a normal distribution would imply that $u(\sigma, \mu)$ satisfies the differential equation

$$\frac{1}{\sigma} \frac{\partial u(\sigma, \mu)}{\partial \sigma} = \frac{\partial^2 u(\sigma, \mu)}{\partial \mu^2} \quad (11)$$

So to summarize the mean/variance analysis, it is clear that it is applicable only with certain restrictions. Additionally, Borch (1969) showed that if preferences satisfy a monotonicity condition, all indifference curves in the mean/variance plane reduce to a single point. Moreover, the motivation for developing an efficient criterion, which is consistent with expected utility ranking, is precisely the nonavailability of the utility function; hence, the assumption of a quadratic utility could only be a special case where

in fact the utility function is quadratic in nature. So for the purpose of this paper we need to look at parametric criteria that are consistent with expected utility rankings, without any assumptions about the functional form of the utility functions or the distribution of the outcome.

It should be evident from the arguments presented above that the assumption of a quadratic utility is generally very restrictive for expected utility representation. According to some arguments presented in the literature, one could relax the assumption of a quadratic utility function, and hence could incorporate higher moments of the distribution. Including the third moment, the skewness, the fourth moment, the kurtosis, which measures the particular aspects of curvature of the distribution function, could extend the mean/variance approach. Although this would describe the distribution more accurately, the mathematical aspect of the model becomes very cumbersome and intractable. Moreover, with a finite number of moments, one cannot accurately describe the distribution. The solution to the problem fortunately exists in the literature. Meyer (1987) discussed a location and scale condition, which, under certain less restrictive assumptions, derives a consistent two-moment (μ, σ) model of expected utility, which is both expected utility and mean-standard deviation (MS) efficient.

CHAPTER 4
CONSISTENT TWO-MOMENT MODELS
OF EXPECTED UTILITY

As is evident from the restrictions above, a quadratic utility function has theoretical defects, and the assumption of normality seems unrealistic in light of the empirical proofs against it. Consequently, the applicability and verifiability of the quadratic utility function are constrained to a small set of feasible problems. With a growing consensus about the lack of congruence between the results of expected utility and mean/standard deviation analysis, there seems to exist a widely accepted condition under which almost any expected utility ranking of outcomes in a choice set can be represented by mean/standard deviation ranking. This condition seems to be sufficient to ensure consistency between the expected utility and mean/standard deviation approaches.

Following Meyer (1987), the decision maker's expected utility ranking of a set of random variables is represented by a ranking based only on their mean and standard deviation, the mean being the location and the standard deviation being the scale parameter. Then expected utility can be represented by two parametric criteria, and would be consistent with the mean/standard deviation ranking. The location and scale parameter condition states that two cumulative distribution functions $F_1(\cdot)$ and $F_2(\cdot)$ are said to differ only by location and scale parameters α and β if $F_1(x) = F_2(\alpha + \beta x)$ with $\beta > 0$.⁸ Simply stated, the consistency condition of interest here is that the choice set be

⁸In our model, α and β can be interpreted as mean and standard deviation, respectively. It becomes clear as we proceed with our analysis.

composed of random variables, which differ from one another only by location and scale parameters. The basic idea is if Y_1, Y_2, \dots, Y_n only differ from each other by location and scale parameters, then the standardized variable x 's obtained from the Y have the same density function. And within this class merely a shift and a proportional extension can transform all distributions into one another.⁹ As $\mu(Y)$ acts as a measure of shift, i.e., as the location parameter, and $\sigma(Y)$ as a measure of extension, i.e., as a scale parameter, around the mean, these two parameters are sufficient to characterize the whole distribution, given the shape of the standardized distribution of the variable x . Thus they can be used for ranking uncertain prospects, which would be consistent with the expected utility efficient set.¹⁰ The connotation of the linear class expected utility expressed as a function of mean and standard deviation, $f(\sigma, \mu)$, is that it is more flexible as neither any assumption has been made about the utility function nor any about the distribution of the random outcome. Moreover, the various restrictions that the location and scale parameter (LS) conditions impose on itself reinforce the arguments for its use for representation of the expected utility conforming to the LS conditions. Even though one could obtain a great deal of comparative static insights using Meyer's (1987) model, empirically the question remains whether the distributions available to the SAES differ only by μ and σ . If they do not, one could use stochastic dominance based on the

⁹The class, which adheres to the location and scale conditions, is also sometimes called as the "linear class."

¹⁰No claims have been made by Meyer (1987) regarding the expected utility and mean/standard deviation efficient sets. Levy (1989) extended Meyer's work and illustrates the conditions under which both expected utility and mean/standard deviation efficient sets are identical, under the assumption of risk-averse and/or all nondecreasing concave utility functions.

expected utility hypothesis to rank random outcomes, which maximizes the expected utility.

To crystallize the idea presented above and to derive the expected utility, let us assume that the random output Y can be characterized by the LS condition. Let x be the standardized normal variable obtained from one of the Y_i , $i \in I = \{1, \dots, n\}$. No matter which Y was selected to obtain x , its density function is the same, this implies that the Y 's conform to the LS conditions,¹¹ where x is defined as

$$x = \frac{(Y_i - \mu_j)}{\sigma_j} \quad (12)$$

and μ_i and σ_i are the mean and standard deviation of Y_i . That is, Y_k and Y_j , $\forall k$ and $j \in I$, differ from one another only by location and scale parameter, and are equal in distribution to $\mu_i + \sigma_i x$, with $E(x) = 0$ and $\sigma(x) = 1$. So the expected utility from Y_i can be written as

$$\begin{aligned} E[U(Y)] &= E[U(\mu + \sigma x)] \\ &\equiv V(\mu, \sigma) \end{aligned} \quad (13)$$

As indicated, equation (13) defines the MS preference function associated with any utility function in an expected utility model. To contemplate the appropriateness of the criteria, we look at the indifference curves in (μ, σ) space. By implicit differentiation of equation (13), and setting $V(\sigma, \mu)$ constant, we get the slope of the indifference curve.

$$\left. \frac{d\mu}{d\sigma} \right|_{V(\sigma, \mu) = \text{const.}} = - \frac{E[xU''(\mu + \sigma x)]}{E[U'(\mu + \sigma x)]}, \quad \text{using } U'(\cdot) = \frac{dU}{d(\cdot)}, \quad (14)$$

¹¹An explicit Kolmogorov-Smirnov statistical test is done later to test if the LS condition holds or not.

$$= - \frac{\text{cov}[x, U'(\mu + \sigma x)]}{E[U'(\mu + \sigma x)]}, \quad (15)$$

where $\text{cov}[x, U']$ is the covariance between x and U' . The assumption of risk averse, $U'' < 0$, implies $\text{cov}(x, U') < 0$ if $\sigma > 0$. Hence,

$$\left. \frac{d\mu}{d\sigma} \right|_{V(\sigma, \mu) = \text{const.}} > 0 \quad \text{for } \sigma > 0. \quad (16)$$

Now, when $\sigma \rightarrow 0$ implies $U'(\mu + \sigma x) \rightarrow U'(\mu)$, this gives

$$\lim_{\sigma \rightarrow 0} \left. \frac{d\mu}{d\sigma} \right|_{V(\sigma, \mu) = \text{const.}} = 0 \quad (17)$$

These aspects of the indifference curves in the (μ, σ) space are perfectly compatible with the Von Neumann and Morgenstern utility index. Due to the concavity assumption of the Von Neumann-Morgenstern function, and convexity of the indifference curves in the (μ, σ) space, it follows that

$$\left. \frac{d^2\mu}{d\sigma^2} \right|_{V(\sigma, \mu) = \text{const.}} > 0. \quad (18)$$

This result excludes the possibility of increasing absolute risk aversion found with the

¹²Using

$$\text{cov}(x, y) = E(xy) - E(x)E(y),$$

thus,

$$E[x, U(\mu + \sigma x)] = \text{cov}[x, U(\mu + \sigma x)] + E[x]E[U(\mu + \sigma x)],$$

since by definition $E[x] = 0$, only the first term in the RHS remain.

¹³For an alternate proof of positivity of the expression, see appendix A. This proof was used by Meyer (1987).

¹⁴For a proof of this, see appendix A.

quadratic utility function. So expected utility could be represented unambiguously as a function of μ and σ , as these two parameters characterize the whole probability distribution. Moreover, as we have neither the restriction of a quadratic utility function, $u(x)$, nor normality of the distribution of $F(x)$, substantial flexibility remains regarding the form that the function $V(\sigma, \mu)$ can take, certainly more flexibility than if quadratic utility or a normally distributed random variable had been assumed.

Having done away with the assumptions of a quadratic utility function and normality of distributions, and conformably deriving the conditions under which expected utility ranking is consistent with mean-standard deviation ranking, we turn our attention to the problem at hand. In this study the SAES, which is assumed to produce research at a minimum cost, holds a portfolio of research that maximizes its expected utility, given a production feasibility constraint.¹⁵ Thereupon we can go ahead and represent the expected utility of the SAES in the μ and σ space and derive conditions under which the optimum portfolio emerges.

¹⁵Production feasibility is "given the resources the feasibility of producing any particular research." It is a convex function, increasing in the output, and decreasing in the inputs. It is discussed in more detail later.

CHAPTER 5
THE MODEL AND SOME COMPARATIVE
STATIC IMPLICATIONS

Given the structure of SAES in most states, I assume that the sole product that it produces is new knowledge and/or new technological advances, that is, it only produces research. It is further assumed that the experiment station scientist(s) knows the cost of each research production decision *ex ante*, but not the output. As a result the experiment station scientist's investment decision yields a random variable denoting the output, Y . In this model the optimizing agent, that is, the SAES director/scientist(s), is assumed to be a utility maximizer, whose utility is a function of the benefits that personally accrue to him/her due to successful completion of a project. The benefits that he/she gets are directly related to the research output, the relationship being that, more knowledge/technological advances produce more benefits that personally accrue to the research-producing agent. Therefore, we can think of the benefit that the maximizing agent personally garners as a monotonic transformation of the realized research output, Y . Benefits that the maximizing agent receives, as I have discussed earlier, could be both pecuniary as well nonpecuniary rewards. These could be monetary rewards, sense of achievement, prestige, professional recognition, etc. In order to maximize his/her own benefits, he/she has to maximize the research output; consequently, the agent tries to maximize the expected utility of the output given a production feasibility constraint. The production feasibility, which is sometimes called the production possibility set, is

the set of all technologically feasible production plans, that is, the technological and financial sufficiency to indulge in a feasible set of a risky research project. The production plan is a *netput* vector with inputs being implicitly negative quantities and output being positive. The research output, Y , in this model is taken to be the published research reports or papers funded by SAES. It is also assumed that at the beginning of every fiscal year, the SAES gets a budget, B , which it allocates between safe investments and risky research projects as it deems fitting.¹⁶ Safe investments could be expanding the administrative infrastructure, buying new equipment, computers, augmenting the extension personnel, etc., and the risk-bearing investments are the research projects undertaken.

Following the general portfolio literature and for a further specification of the approach, it is assumed that there is one safe category and n risk-bearing research projects to invest in. A unit of money invested in the safe category contributes Y^s to the research output at the end of the financial year, and a unit of money invested in the j th risk-bearing research project contributes Y_j^r , $j = 1 \dots n$ to the research output at the end of the fiscal year. Let the proportion of budget, B , invested in the safe asset be γ^s and in all the risk-bearing research projects be γ^r . Let the proportion invested in the j th risk-bearing research project come out of the amount that is invested in all of the research projects, γ_j^r , i.e., $\sum_{\forall j} \gamma_j^r = 1$.¹⁷ Since the production choice has to be made from all

¹⁶The concept of a financial year does not have any implications for the length of the time period. The time period could take on any economically relevant time interval.

¹⁷The budget is divided into safe and risky investments; likewise risky investments are divided among n risky research projects. The gammas are in proportions, so $\gamma^s + \gamma^r = 1$; furthermore, as γ_j^r are the

feasible γ 's to maximize the expected utility, we can therefore define an envelope function to represent the maximized value of the expected utility as

$$\Phi[\gamma^s, \gamma^r, \gamma^i] = \max_{\gamma^s, \gamma^r} \left\{ [U(B(\gamma^s Y^s + \gamma^r \sum_{j=1}^n \gamma_j^r Y_j^r))] \mid g[(Y), (\gamma^s + \sum_{j=1}^n \gamma_j^r \gamma_j^r)] = 0 \right\}, \forall j=1 \dots n. \quad (19)$$

In the Expected Envelope Utility Function, $\Phi[\cdot]$, the production feasibility is expressed as the constraint $g[\cdot]$, a convex function increasing in Y and decreasing in the γ 's.¹⁸ The output is defined as $Y = B[\gamma^s Y^s + \gamma^r \sum_{j=1}^n \gamma_j^r Y_j^r]$, where B , is the total budget for a fiscal year. As per our discussion about consistent two moment models of expected utility in chapter 4, it is assumed that Y 's differ from each other only by $\mu + \sigma x$, where $x = \frac{(Y - \mu)}{\sigma}$, and obtained from a normalizing transformation of any Y . This implies that Y complies with the "location and scale conditions," or, as it is sometimes called, it belongs to a "linear class." Therefore, without making any assumptions about the functional form of the utility function or about the distribution of the research output, one can represent the expected utility as a function of only two parameters μ and σ , where μ is the mean and σ is the standard deviation of the random research output. These two parameters, one being the location, which is the shift parameter, and one

proportions from the total risky investments, that is, γ^r , hence $\sum \gamma_j^r = 1$. This kind of representation is to separate the optimal structure of the risk-bearing research project from division of funds between risky and safe investments. This is Tobin's (1958) well-known Separation Theorem, which will be briefly discussed later in the model.

¹⁸The idea of an envelope function to define a utility function was first introduced by Meade (1951). It has the name "Meade Utility Function," in recognition of his geometric treatment of indifference curves defined on net trades.

being the scale, which is the extension parameter, are enough to characterize the whole distribution of the random research output. So the expected utility of Y can be expressed as

$$\begin{aligned} E[U(Y)] &= E[U(\mu + \sigma x)] \\ &\equiv V(\sigma, \mu) \end{aligned} \quad (20)$$

Since the agent maximizes the expected utility of the output, the maximizing problem of the SAES can be represented as

$$\max_{\gamma^s, \gamma_j^r} \left\{ V(\sigma, \mu) \mid g[(\mu, \sigma), (\gamma^s, \sum_{i=1}^n \gamma_i^r)] \right\}, \quad (21)$$

where $V(\sigma, \mu)$ describes a system of positively sloping convex indifference curves in the (μ, σ) space. For the needed distribution parameters, σ and μ , we calculate

$$\begin{aligned} \mu \equiv E(Y) &= B[\gamma^s Y^s + \gamma^r \sum_{j=1}^n \gamma_j^r E(Y_j^r)] \\ &= B[\gamma^s Y^s + \gamma^r E(Y^r)] \end{aligned} \quad (22)$$

and

$$\begin{aligned} \sigma \equiv \sigma(Y) &= B\gamma^r \sqrt{\sum_{i=1}^n \sum_{j=1}^n \gamma_i^r \gamma_j^r \rho_{ij} \sigma(Y_i^r) \sigma(Y_j^r)}, \\ &= B\gamma^r \sigma(Y^r) \end{aligned} \quad (23)$$

where $\rho_{ij} = \frac{\text{cov}(Y_i^r, Y_j^r)}{\sigma(Y_i^r) \sigma(Y_j^r)}$ is the coefficient of correlation between research project i

and j .¹⁹

¹⁹In the above equation, the expectation of Y^s is not taken as it is not random, and its value is known ex ante.

To maximize the objective, first the optimal structure $\gamma_1^r, \gamma_2^r, \dots, \gamma_n^r$ of the risk-bearing research portfolio is determined, and then the division of funds between γ^r and γ^s is determined. This is a well-known result of Tobin (1958) that is generally referred to as the Separation Theorem. To gain some insight about the optimal structure, the maximization problem is represented as a Lagrangean

$$L = V(\sigma, \mu) - \lambda \cdot g[(\sigma, \mu), (\gamma^s + \sum_{i=1}^n \gamma^r \gamma_i^r)] \quad (24)$$

Since Y is a function of γ 's, the mean and standard deviation of Y will also be dependent on the γ 's, formally $\mu = \mu(\gamma^s, \gamma^r, \gamma_i^r)$ and $\sigma = \sigma(\gamma^r, \gamma_i^r)$, and define $W = \gamma^s + \sum_{i=1}^n \gamma^r \gamma_i^r$.

The definition of W does not compromise the problem in any way; rather it makes the mathematical maneuvers much more tractable. Assuming an interior solution to the maximizing problem, the first-order conditions are

$$\frac{\partial L}{\partial \gamma^s} = \frac{\partial V}{\partial \mu} \frac{\partial \mu}{\partial \gamma^s} - \lambda \left\{ \frac{\partial g}{\partial \mu} \frac{\partial \mu}{\partial \gamma^s} + \frac{\partial g}{\partial W} \right\} = 0 \quad (25)$$

and

$$\frac{\partial L}{\partial (\gamma^r \gamma_k^r)} = \frac{\partial V}{\partial \mu} \frac{\partial \mu}{\partial (\gamma^r \gamma_k^r)} + \frac{\partial V}{\partial \sigma} \frac{\partial \sigma}{\partial (\gamma^r \gamma_k^r)} - \lambda \left\{ \frac{\partial g}{\partial \mu} \frac{\partial \mu}{\partial (\gamma^r \gamma_k^r)} + \frac{\partial g}{\partial \sigma} \frac{\partial \sigma}{\partial (\gamma^r \gamma_k^r)} + \frac{\partial g}{\partial W} \right\} = 0. \quad (26)$$

To compare the effect of a marginal increase in the research output, due to an increase in the k th risk-bearing research project with its additional cost, equations (25) and (26) are set equal to each other, and by canceling out the λ 's, the following is obtained

$$\frac{\partial \mu}{\partial (\gamma^r \gamma_k^r)} - \frac{d\gamma^s}{d(\gamma^r \gamma_k^r)} \Big|_{g(.)=const.} \quad \frac{\partial \mu}{\partial \gamma^s} = - \frac{d\mu}{d\sigma} \Big|_{V(.)=const.} \cdot \frac{\partial \sigma}{\partial (\gamma^r \gamma_k^r)}, \quad (27)$$

where

$$\frac{d\mu}{d\sigma} \Big|_{V(.)} = \frac{\partial V}{\partial \sigma} \quad \text{and} \quad \frac{d\gamma^s}{d(\gamma^r \gamma_k^r)} \Big|_{g(.)} = \frac{\frac{dg(.)}{d(\gamma^r \gamma_k^r)}}{\frac{d\gamma^s}{d\gamma^s}}. \quad (28)$$

Equation (27) is very similar to Sinn's (1989) optimality rule, but with an additional term, which is the marginal rate of technical substitution between safe and risky investments. This rule compares the additional increase in the research output with its additional cost. An increase in the research output is an increase in the expected value of the random research output due to changes in the investment structure between the safe category and risk-bearing research projects. Correspondingly, cost can be interpreted as changes in the standard deviation, σ , due to changes in investments in the k th risk-bearing research project, and also a total change in the expected value of the random research output can be due to change in the riskiness as embodied in the standard deviation, σ . More precisely, if the proportion of the safe investment is reduced by one percentage due to one percentage increase in the proportion the k th risky research project, then the total research output increases by $\frac{\partial \mu}{\partial (\gamma^r \gamma_k^r)} - \frac{d\gamma^s}{d(\gamma^r \gamma_k^r)} \Big|_{g(.)} \frac{\partial \mu}{\partial \gamma^s}$. The

cost of restructuring the research portfolio depends on $\partial \sigma / \partial (\gamma^r \gamma_k^r)$, that is, how the standard deviation is affected by an increase in the proportion invested in the k th risk-

²⁰For the derivation of the rule, see appendix A.

bearing research project. In addition to that, there is the price of risk or price of an additional unit of standard deviation, which is represented by the term $d\mu/d\sigma|_V$.

In the portfolio literature, this price, $d\mu/d\sigma|_V$, has been interpreted as the amount by which the expected value of the outcome has to increase due to a unit increase in the standard deviation. This interpretation, although correct, has led to an erroneous conclusion, as pointed out by Sinn (1989), that the size of $d\mu/d\sigma|_V$ depends on the agents' preferences. Consider an opportunity locus in the (μ, σ) plane, consisting of a continuum of points, each of which represents one of the attainable research output distributions. By use of the indifference curves and tangency solution, one point at least on this boundary is found to be optimal. Hence, $d\mu/d\sigma|_V$, in fact, is equal to the slope of the efficiency frontier, that is, the maximum value of $[E(Y^r) - Y^s]/\sigma(Y^r)$, to which it is adapted by a variation of γ^s , as shown in figure 3.²¹

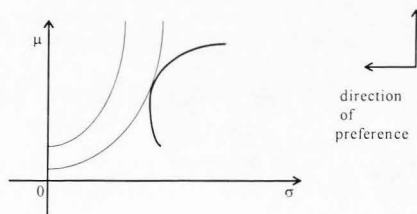


FIG. 3.—Optimal research portfolio choice given the decision maker's preference structure.

²¹ $[E(Y^r) - Y^s]/\sigma(Y^r)$. This term attains a maximum when $E(Y^r)$ is at its maximum, and when Y^s and $\sigma(Y^r)$ are at their minimum.

The variation in γ^s basically implies the substitutability between the safe and risky investments. Even though Sinn identified the concept, his portfolio framework did not allow him to explicitly identify the degree of variation required by γ^s .

PROPOSITION 1. Given a production feasibility constraint and positive and finite μ and σ , the increase in the expected value of research output due to a decrease in the proportion invested in the safe category has to be scaled by the marginal rate of technical substitution between the safe and risky holdings for $d\mu/d\sigma|_V$ to be equal to the slope of the efficiency frontier.

This proposition is clearly defined in equation (27) and becomes clear once we take a look at this particular equation. It gives an expression, which gives the optimal increase in the total expected value²² of the research output to compensate for an unit increase in the riskiness as measured by the standard deviation. Consequently, the condition that equates the slope of the indifference curve with the efficiency frontier. According to rule an additional increase in the research output to be equated with the cost, that is, the RHS of equation (27), the change in μ due to a change in the proportion invested in the safe category has to be scaled by $d\gamma^s/d(\gamma^r\gamma_k^r)|_{g(\cdot)}$. That is, the marginal rate of technical substitution (MRTS) between proportion invested in the safe category and risk-bearing research project as demonstrated by equation (28). That is, the slope of the indifference curve becomes equal to the efficiency frontier; hence we can find at least one distribution that gives the maximum expected utility.

²²Increase in total expected value is due to investments in k th risky research project as well as in the safe category.

To determine what equation (27) implies for the size of the proportion invested in the k th risk bearing research project, γ_k^r , every term of the above equations is calculated separately from equations (22) and (23), and then substituted back into equation (27) and solved to get an expression for γ_k^r .²³

$$\gamma_k^r = \frac{\frac{E(Y_k^r) + Y^s \frac{dY^s}{d(\gamma_k^r \gamma_k^r)} \Big|_{g(\cdot)}}{\sigma(Y_k^r)} \frac{d\mu}{d\sigma_{V(\sigma, \mu)}}}{\frac{\sigma(Y^r)}{\sigma(Y_k^r)} - \frac{\sum_{\substack{i=1 \\ i \neq k}}^n \gamma_i^r \rho_{ik} \sigma(Y_k^r) \sigma(Y_i^r)}{\sigma^2(Y_k^r)}} \quad (29)$$

Even if we do not get an explicit solution for γ_k^r , since $d\mu/d\sigma_V$ and $\sigma(Y^r)$ depend on γ_k^r , we can still meaningfully interpret the result. If we set all of the coefficient of correlation with $i \neq k$ equal to zero, then the second term on the RHS disappears. The first term relates the price of risk specific to the k th research project,

$$\frac{E(Y_k^r) - Y^s \frac{dY^s}{d(\gamma_k^r \gamma_k^r)} \Big|_{g(\cdot)}}{\sigma(Y_k^r)}, \text{ to the average price of risk } d\mu/d\sigma_V \text{ of the total portfolio.}$$

Since the average price of risk of the total portfolio is positive ($d\mu/d\sigma_V > 0$), and by

$$\text{definition } \sigma(Y^r)/\sigma(Y_k^r) > 0, \text{ we find } \frac{E(Y_k^r) - Y^s \frac{dY^s}{d(\gamma_k^r \gamma_k^r)} \Big|_{g(\cdot)}}{\sigma(Y_k^r)} > 0 \text{ to be a necessary and}$$

sufficient condition for $\gamma_k^r > 0$. This result is very similar to the most important result of

²²Increase in total expected value is due to investments in k th risky research project as well as in the safe category.

²³To see the derivation of equation (29), see appendix A.

Markowitzian portfolio theory. But note that it does not imply that all risky research projects that promise a higher expected outcome than the safe investment are included in the portfolio.

PROPOSITION 2. Given a production feasibility constraint, and a positive and finite μ and σ , all risky research projects that promise a higher expected outcome than the safe investment scaled by the marginal rate of technical substitution between safe and risky research investments will enter the optimal portfolio.

Proposition 2 is self-explanatory and follows from equation (29). This equation implies that given the positivity of $d\mu/d\sigma_V^1 > 0$ and $\sigma(Y_k^r)/\sigma(Y_k^s) > 0$, γ_k^r will be positive if and only if the expected value of the k th research prospect is greater than the return from the safe category scaled by the marginal rate of technical substitution between risky research investments and safe investments. So if $\gamma_k^r > 0$, then the k th research prospect will enter the portfolio. Hence it is not only the project with the highest expected outcome that enters the portfolio, but rather all risky research projects that promise a higher expected return than the safe investment scaled by the marginal rate of technical substitution are included.²⁴

The use of location and scale provides a much more powerful tool than the traditional mean variance approach for comparative static analysis. However, whether the random distributions differ from each other only by μ and σ is an empirical question. To test this hypothesis, a test introduced by Meyer and Rasche (1992) was used. This test is based

²⁴Of course, the results drastically change if the coefficient of correlation is not set to zero. So, as long as independence of research projects is assumed, that is, project k and project j are not correlated, then we can set the correlation coefficient to zero.

on the multisample Kolmogorov-Smirnov (KS) statistic, D , that is, the maximum difference between any pair of $F(\cdot)$ empirical distribution functions. Formally, if the distribution of the random research publication per research dollar, Y_i , satisfies the location and scale conditions, that is, if the data are likely results from observing Y_i , which will satisfy $Y_i = \mu + \sigma x_i$, where μ is the mean and σ is the standard deviation of Y_i . Since x_i is a normalized variable with zero mean and constant unit variance, it is a white noise process. And since x_i belongs to the same distribution function no matter which Y_i was selected to obtain it, then all x_i from respective Y_i should be a white noise process.

To test the hypothesis that the EDFs (empirical distribution functions) of Y_i do in fact differ from each other only by location and scale, all the x_i s were estimated using the observed Y_i s. The multisample Kolmogorov-Smirnov test was used to find the test statistics $D = \sup[F(x_i) - G(\text{white noise})]$, where $F(x_i)$ is the distribution function for x_i and $G(\cdot)$ is a white noise process. The decision rule being, if the supremum, D , is larger than the critical value, then reject the hypothesis that the Y_i s differ from each other only by μ and σ or, in other words, location and scale. KS test statistics run on the normalized x_i s yielded many rejections of the null hypothesis that the empirical distributions are identically distributed up to location and scale parameters. Since the KS test suggests that traditional mean variance analysis would be inappropriate, the more general method of stochastic dominance is employed.

CHAPTER 6

STOCHASTIC DOMINANCE AND ITS APPLICABILITY

Since, in most empirical investigations, we fail to accurately assess the decision maker's utility function and/or struggle with the problems associated with the mean/variance approach, empirical attention has shifted more towards comparisons of the probability distributions of the research outcome that are based only on the limited information about the decision maker's utility function. The rationale behind calculating the efficient or nondominated set is precisely the nonavailability of the utility function. If such a function could be measured and formulated, then it should be applied directly to the set of available alternative outcomes. It is then reasonable to assume that the utility function is unknown, barring a few general properties such as being nondecreasing, monotonic, risk averse, etc.

The criterion for comparison of different probability distributions is known as stochastic dominance. This allows the ranking of distributions for different classes of risk attitudes. Suppose that all that is known about the decision maker's utility function can be described by a set U of real valued functions such that $u \in U$. If $\int u dF > \int u dG \quad \forall u \in U$, and F and G are distribution functions, then F is said to "stochastically dominate" G with respect to U . This dominance of one probability distribution over the other implies $F >_i G$ iff $E(u, F) > E(u, G)$, $i = 1, 2, 3, \dots$, where $i = 1, 2, 3, \dots$ denotes the different degrees of stochastic dominance, 1 being first degree stochastic dominance, 2 being second degree, and so on. That is, for a distribution F to dominate distribution G , it is

necessary and sufficient that the expected utility associated with the distribution F be higher than that associated with G . A particularly good synthesis of stochastic dominance can be found in Bawa (1975). It is assumed that the agent is rational and obeys the axiomatic behavior prescribed by Von Neumann and Morgenstern (1953). These are basically the ordering postulates and monotone continuity. Under these assumptions, the SAES director/scientist(s) chooses the alternative, which maximizes the expected utility of the random research output, where the utility function is determined uniquely, up to a positive linear transformation. Because complete information about individual preferences (i.e., his/her utility function) is seldom available, we use stochastic dominance (SD) rules that provide a one-to-one correspondence between the maximum expected utility rule for certain classes of utility functions and the rules for pair-wise comparisons between the probability distributions.

Three types of dominance seem to be useful for the analysis of a variety of decision problems under uncertainty. The strongest of these conditions is referred to as first-degree stochastic dominance (FSD). Quirk and Saposnik (1962), Hadar and Russell (1969, 1971), Hanoch and Levy (1969) and Fishburn and Vickson (1978) obtained a selection rule for the entire class $u_i \subset U$ of increasing real value utility functions. This rule holds that whenever one cumulative distribution lies, at least partly, under the other cumulative distribution and the distributions never cross, then the dominant distribution is said to be larger than the other distribution in the sense of FSD. If the two cumulative distributions are $F(x)$ and $G(x)$, and defined over any interval I , we say:

if $F(x) \leq G(x) \quad \forall x \in I$, the strict inequality holding for at least one x , then F is larger than G in the sense of FSD.

A weaker dominance condition is called second-degree stochastic dominance (SSD). Since the decision maker, the station director/scientist(s), is assumed to be risk averse, such behavior generates a class of utility functions $u_2 \subset u_1$, with negative second derivatives. SSD captures the downside risk aversion, that is, people are averse to adverse shocks. Hadar and Russell (1969, 1971) and Hanoch and Levy (1969) derived the SSD rule, and this holds whenever the area under one cumulative distribution is everywhere not greater than that under the other distribution. Again, considering the distributions defined over any interval I , we say:

$$\text{if} \quad \int F(x)dx \leq \int G(x)dx \quad \forall x \in I \quad (30)$$

the strict inequality holding for at least one x , then F is larger than G in the sense of SSD.

For the class $u_3 \subset u_2$, characterized by a positive third derivative and a finite range, Whitmore (1970) obtained the optimal selection rule and called it third-degree stochastic dominance (TSD), and this holds for the second integral of SSD. Formally, we can write it as

$$\iint F(x)dxdt \leq \iint G(x)dxdt \quad \forall x \in I \quad (31)$$

the strict inequality holding for at least one x , then F is larger than G in the sense of TSD

and where $\{u_3 \subset u_2 : U'''(x) \geq 0 \quad \forall x\}$. The requirement that U''' be positive is motivated by noting that this is a necessary condition for decreasing absolute risk aversion (DARA).

Bawa (1975) showed that for distributions with the same mean, third-degree stochastic dominance is precisely equivalent to preference by all utility functions displaying DARA.

Given the rules of stochastic dominance it can be effectively used to determine the non-dominated set, that is, to isolate the set of alternatives with the maximum expected utility derivable from research output. By using these rules the available possibilities are divided into efficient and inefficient sets. The efficient and inefficient sets are defined as follows, a research possibility B belongs to the inefficient set if there is at least one possibility A among all the feasible possibilities such that a decision maker having a utility function from the restricted class would prefer A to B. Therefore, only the core of the prospects not ruled out by the SD remains in the efficient set.

CHAPTER 7

THE DATA, APPLICATION OF STOCHASTIC DOMINANCE,
AND TEST RESULTS

The publication data were compiled from the AGRICOLA database and the USDA's (various years [a]) *Bibliography of Agriculture*. From these two sources, all the published papers and reports were identified, which were funded by each of the 10 western SAESs—Arizona, California, Colorado, Idaho, Kansas, Montana, Nevada, New Mexico, Oregon, Utah— over the period 1967-91. The title and descriptors of each paper were reviewed and each paper assigned to one of the 19 research categories: 1—feed grains (incl. corn, forage); 2—food grains (e.g., rice, wheat); 3—oil crops (e.g., cotton seeds, peanuts); 4—fruits and nuts; 5—vegetables (incl. potatoes); 6—cotton; 7—tobacco; 8—meat animals (incl. fish, game, bee); 9—dairy product (incl. dairy cattle); 10—poultry; 11—other crops (e.g., ornamental); 12—forest and forest products; 13—soil, water, air, and climate; 14—recreation; 15—technology of production; 16—agriculture in society; 17—agriculture enterprise; 18—weeds, seeds, and bugs; and 19—basic research. Annual research expenditures on each of these categories for all the states were collected from USDA's (various years [b]) *Inventory of Agricultural Research*. From the time of allocation of funds to a particular research project until the time a publication is cataloged, it is assumed that there is a three-year lag. Recognizing that publication often lags funding outlays, a three-year-lagged moving average of published-paper-or-report-per-research-dollar was used. I compare the alternative uses

of research funds within several different sets, the 10 experiment stations, the 19 research categories, the 23 years, research categories within each state, and states within each research category.

I. Application of Stochastic Dominance

Given the data and the stochastic dominance rules, we need to reformulate the SD rules such that they can be directly applied to the data. The expenditure on any specific research category is referred to as investment and the number of published papers or reports in a category within a specific year is referred to as the return to the investment.

Since I am working with a discrete random variable, that is, research output, the SD rules have to be redefined. Therefore, before conducting any SD test, we need to discretize the definition for the continuous case. To approximate the underlying distribution function of the research output, the analog principle is used that shows that the sample frequency distribution corresponds to the probability distribution function in the population.

In accordance to the arguments presented above, the SD rules can be formulated as follows: if the station's utility is increasing in papers and/or reports published, then the station director would unambiguously prefer category A to category B,

$$\text{iff} \quad D_1(y_j) = \sum_{y_i \leq y_j} B(y_i) - \sum_{y_i \leq y_j} A(y_i) \geq 0 \quad \forall y_j \quad (32)$$

$$j = 1, \dots, n \text{ and } y_j \in \mathcal{Y}^*$$

where Y_i is the research publications per research dollar. Also, if the difference between the cumulative probability function for the discrete distribution $B(y_j)$ and $A(y_j)$ is greater

than or equal to zero and strictly greater for at least one j , then the discrete cumulative distribution $A(y_j)$ lies everywhere below the discrete cumulative distribution $B(y_j)$. Hence, category A dominates category B in the first-degree stochastic dominance sense (FSD). Therefore, any utility-maximizing station director will choose to invest more in category B.

The second-degree stochastic dominance uses the results from the FSD. The station director will prefer category A to category B,

$$\text{iff } D_2(y_j) = \sum_{y_i \leq y_j} D_1(y_{i-1}) \geq 0 \quad \forall y_j \quad (33)$$

$$j = 1, \dots, n \text{ and } y_j \in \mathcal{Y}$$

that is, if the discrete cumulative probability function crossover and the total area between the curve (FSD curve) are greater than zero, then the area under the discrete distribution of category A, which is less than the area under the discrete distribution of category B, implies A second-degree stochastically dominates B.

Third-degree stochastic dominance, which is a necessary condition for DARA, uses the SSD results. Category A is said to dominate category B in the third-degree stochastic dominance sense,

$$\text{iff } D_3(y_j) = \sum_{y_i \leq y_j} D_2(y_{i-2}) \geq 0 \quad \forall y_j \quad (34)$$

$$j = 1, \dots, n \text{ and } y_j \in \mathcal{Y}$$

Given the rules of stochastic dominance for the discrete case, the tests were run and the results tabulated.

II. The Results

First, consider the U.S. Secretary of Agriculture's (USSA) choices of allocation of aggregate national funds across different SAESs and among the 19 research areas. Table 1 presents the results of FSD and SSD tests for stylized choice. I pooled time-series observations on research publication per thousands of research dollar expenditure across states in the case of the set, S_R , of the 19 research categories and across research categories for the set, S_W , of 10 states. Under FSD, the results show a first-level efficiency set comprised of research on forestry; production technology; weeds, seeds, and bugs; and basic research (categories 12, 15, 18, and 19) and research conducted in

TABLE 1
UNCONDITIONAL STOCHASTIC DOMINANCE TESTING RESULTS

EFFICIENCY SET	RANKING AMONG SAES		RANKING AMONG RESEARCH AREAS	
	FSD	SSD	FSD	SSD
Most efficient	CO,NM,NV,UT	NM,UT	12,15,18,19	12,15,18,19
	ID,OR	CO	4,10,14,16,17	16
	AZ,MT	ID,NV	1,11	4,17
	KS	OR	2,8,13	1,10,14
	CA	MT	5,6	11,13
		AZ	9	2
		KS	3,7	8
		CA		5
				6
				9
Least efficient				3,7

New Mexico and Utah. Imposing the assumption of risk-averse preferences, the first-level efficiency set of SAES reduces to New Mexico and Utah.

Repeating the exercise at the state level, trying to identify for each state which research areas offer the most attractive research publication per thousands of research dollar distributions generates similar results (table 2). In nine out of 10 states, the first-best efficiency sets include at least one of the top four categories nationally (12, 15, 18, and 19); and in seven of the 10 states, the first-level efficiency set is comprised entirely of those research areas.

TABLE 2
RESEARCH AREA EFFICIENCY SETS BY STATE

STATES	FIRST-BEST EFFICIENCY SET		SECOND-BEST EFFICIENCY SET	
	FSD	SSD	FSD	SSD
Arizona	6,12,15,17,18	15,18	19	12,17
California	12,18	12	10,17	17,18
Colorado	4,12,15,18,19	4,12,18,19	1,10,16	15
Idaho	14,15,18	15,18	12,16,17,19	12,14,16,17
Kansas	15	15	18,19	19
Montana	19	19	12	12
Nevada	16,17	16	1,15,19	1,15,17,19
New Mexico	15	15	14,16,17,18,19	14,16,17,18,19
Oregon	12	12	15,17	15,17
Utah	10,18,19	19	12,15,16	12,16,18

To test the hypothesis that the productivity distribution of publication per research dollar improves over time, the observations were pooled across research categories and SAES for each year and FSD and SSD tests were done among the years 1969-91. The exercise was repeated for each state, pooling observations only across 19 research categories (see appendices B and C). The results suggest that the mid-1970s were years of peak research publications output per SAES dollar outlay, with 1975 and 1976 representing the first-level efficiency set under SSD.

The most recent years, 1988-91, are dominated by all the others in a SSD sense, implying that SAES research productivity has fallen. That pattern is largely mirrored at state levels, with the notable exceptions of Idaho, where 1990 and 1991 are in the first-level efficiency set under FSD, and Nevada and Utah, where the most recent years are in the middle of the rank ordering of year distributions.

Out of concern for the efficient use of public research funds, there is considerable current discussion about merits and means of introducing regional centers of research excellence in specific fields. Stochastic dominance analysis of data pooled across years can provide crucial information on the relative strengths of different SAESs within each of the 19 research categories. It is apparent that the low ranking of the big agricultural states—California, Kansas—mirrors similarly poor rankings conditional on research area. Likewise, some SAESs are clearly superior within the region in particular fields (e.g., Arizona in cotton, Oregon in forestry, see table 3) despite mediocre rankings overall. The leading states in the unconditional rankings (table 1) clearly achieve this by

broad-based excellence. The SAESs in New Mexico and Utah, for example, are each undominated in both FSD and SSD senses in at least 10 of the 19 categories. Hence they are in the top regional ranking in research productivity per dollar expenditure.

TABLE 3
SAES ABSOLUTE ADVANTAGE RANKINGS

RESEARCH AREA	FIRST-BEST EFFICIENCY SET		SECOND-BEST EFFICIENCY SET	
	FSD	SSD	FSD	SSD
1: Feed grains	NM, UT	UT	CO	CO, NM
2: Food grains	CO, NM, UT	UT	MT	CO, NM
3: Oil crops	CO	CO	NM	NM
4: Fruits/nuts	No ordering	No ordering	No ordering	No ordering
5: Vegetables	NM	NM	CO	CO
6: Cotton	AZ, NM	AZ, NM	All the rest	All the rest
7: Tobacco	No ordering	No ordering	No ordering	No ordering
8: Meat animals	CO, NM, NV	CO, NM, NV	OR	OR
9: Dairy	UT	UT	ID	ID
10: Poultry	NM, UT	NM, UT	CO, MT	CO, MT
11: Other crops	NV, UT	UT	CO, NM	CO, NM
12: Forest	OR	OR	CO	CO
13: Soil, water, etc.	NM	NM	ID, NV	ID, NV
14: Recreation	ID, NM	NM	UT	ID, UT
15: Prod. & techn.	NM	NM	CO, ID, UT	CO, ID, UT
16: Ag. in society	NM, NV, UT	NM, NV, UT	CO, ID	CO, ID
17: Ag. business	ID, NM, NV	NM, NV	OR, UT	ID, OR, UT
18: Weeds/seeds	UT	UT	CO	CO
19: Basic	UT	UT	CO, MT, NM, NV	CO, NV

CHAPTER 8

CONCLUSIONS

While considerable attention has been given to estimation of rates of return to public agricultural research expenditure in aggregate, surprisingly little work has been done on the optimal allocation of public research budgets. This paper demonstrates one useful method of analysis, presenting stochastic dominance testing results on the research publication returns per dollar expended in each of 10 western U.S. state agricultural experiment stations over the period 1967-91. The results suggest there are marked differences—across states and research categories—in the scholarly productivity of public agricultural research expenditures. It also appears that productivity has generally been declining over time. Finally, we demonstrate how SD analysis can be used to reveal absolute advantage between the SAES in particular research areas, as well as between the research areas within each SAES. These findings and the methods that generate them may be useful at both national and state levels if serious efforts are to be made toward emphasizing regional centers of research excellence in particular fields.

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Whitmore, G. A. "Third-Degree Stochastic Dominance." *Amer. Econ. Rev.* 60 (1970): 457-9.

APPENDICES

Appendix A: Mathematical Derivations

Proof 1.1. Equation (8) can be written as

$$\omega\mu^2 - \mu + \omega\sigma^2 = -E[u(Y)] \quad (8.1)$$

$$\Rightarrow \omega\left[\mu^2 - \frac{\mu}{\omega}\right] + \omega\sigma^2 = -E[u(Y)] \quad (8.2)$$

$$\Rightarrow \mu^2 - \frac{\mu}{\omega} + \sigma^2 = -\frac{E[u(Y)]}{\omega} \quad (8.3)$$

$$\Rightarrow \mu^2 - \frac{\mu}{\omega} + \frac{1}{4\omega^2} - \frac{1}{4\omega^2} + \sigma^2 = -\frac{E[u(Y)]}{\omega} \quad (8.4)$$

$$\Rightarrow \left[\mu - \frac{1}{2\omega}\right]^2 + \sigma^2 = \frac{1}{4\omega^2} - \frac{E[u(Y)]}{\omega} \quad (8.5)$$

Equation (8.5) is the equation of a circle, centered at $(0, 1/2\omega)$, with radius

$$\sqrt{\frac{1}{4\omega^2} - \frac{E[u(Y)]}{\omega}} \quad (8.6)$$

QED

Proof 1.2. If the outcome is a continuous random variable, with support from a to b , we can write $E[xU'(\mu + \sigma x)]$ as

$$E[xU'(\mu + \sigma x)] = \int_a^b xU'(\mu + \sigma x)d\psi(x) \quad (15.1)$$

where $U(\cdot)$ is the utility function and $\psi(x)$ is the distribution function. So (15.1)

$$\Rightarrow \int_a^b U'(\mu + \sigma x)xd\psi(x) \quad (15.2)$$

Integrating the above equation by parts,

$$\Rightarrow U'(\mu + \sigma x) \int_a^b x d\psi(x) \Big|_a^b - \sigma \int_a^b \left\{ U''(\mu + \sigma x) \int_a^x t d\psi(t) \right\} dx \quad (15.3)$$

$$\Rightarrow U'(\mu + \sigma x) \Big|_{x=b}^b \int_a^b x d\psi(x) - U'(\mu + \sigma x) \Big|_{x=a}^a \int_a^b x d\psi(x) - \sigma \int_a^b \left\{ U''(\mu + \sigma x) \int_a^x t d\psi(t) \right\} dx \quad (15.4)$$

since $\int_a^b x d\psi(x) = 0$, as it is the mean of a standard normal variable 'x', then equation

(15.4) collapses to

$$E[xU'(\mu + \sigma x)] = -\sigma \int_a^b \left\{ U''(\mu + \sigma x) \int_a^x t d\psi(t) \right\} dx \quad (15.5)$$

Thus

$$\text{cov}[x, U'(\cdot)] = E[xU'] = -\sigma \int_a^b \left\{ U''(\cdot) \int_a^x t d\psi(t) \right\} dx \quad (15.6)$$

Due to the assumption of a risk averse agent, i.e., a concave utility function hence $U' > 0$ and $U'' < 0$. As x is a standard normal variable it has a expected value of zero i.e., $E(x) = 0$, which implies that $\int_a^x t d\psi(t) \leq 0$, and σ is assumed to be greater than zero i.e., $\sigma > 0$.

Then it follows that $\text{cov}[x, U'] < 0$.

If the covariance between x and U' is negative, it implies that the slope of the indifference curve is positive, formally

$$\left. \frac{d\mu}{d\sigma} \right|_{V(\sigma, \mu) = \text{const.}} = \sigma^a \frac{\int_a^b \left\{ U''(\cdot) \int_a^x t d\psi(t) \right\} dx}{\int_a^b U'(\cdot) d\psi(x)} > 0 \quad (15.7)$$

Equation (15.7) is nothing but equation (15) in the main body of the text, i.e.,

$$-\frac{\text{cov}[x, U'(\mu + \sigma x)]}{E[U'(\mu + \sigma x)]} > 0$$

QED

Proof 1.3. To prove that equation (18) is positive, that is

$$\left. \frac{d^2 \mu}{d\sigma^2} \right|_{V(\sigma, \mu)} > 0 \quad (18.1)$$

This property follows from a strictly concave Von Neumann-Morgenstren function, that is, from $U'' < 0$. Tobin (1958) first pointed this out. To drive home the point, consider two indifferent points (μ_1, σ_1) and (μ_2, σ_2) , which are both situated on the same indifference curve. This indifference curve is strictly convex if and only if, for any pair of such points

$$(\mu_1, \sigma_1) \sim (\mu_2, \sigma_2) < \left(\frac{\mu_1 + \mu_2}{2}, \frac{\sigma_1 + \sigma_2}{2} \right) \quad (18.2)$$

The assumption of a strict concave utility function in turn implies

$$\frac{U(\mu_1 + \sigma_1 x)}{2} + \frac{U(\mu_2 + \sigma_2 x)}{2} \leq U\left(\frac{\mu_1 + \sigma_1 x}{2} + \frac{\mu_2 + \sigma_2 x}{2}\right) \quad (18.3)$$

where the inequality sign holds strictly for all x , except for the case where $\mu_1 + \sigma_1 x = \mu_2 + \sigma_2 x$. Applying the expectation operator, we get

$$\frac{E[U(\mu_1 + \sigma_1 x)]}{2} + \frac{E[U(\mu_2 + \sigma_2 x)]}{2} \langle E \left[U \left(\frac{\mu_1 + \mu_2}{2} + \frac{\sigma_1 + \sigma_2}{2} x \right) \right] \right. \quad (18.4)$$

By assumption, (μ_1, σ_1) and (μ_2, σ_2) are chosen such that $E[U(\mu_1, \sigma_1 x)] = E[U(\mu_2, \sigma_2 x)]$, hence,

$$E[U(\mu_1 + \sigma_1 x)] = E[U(\mu_2 + \sigma_2 x)] \langle E \left[\left(\frac{\mu_1 + \mu_2}{2} + \frac{\sigma_1 + \sigma_2}{2} x \right) \right] \right. \quad (18.5)$$

This expression has the same meaning as equation (18.2), and since it holds for any pair of different points on an indifference curve, it proves equation (18) in the paper.

QED

Proof 1.4. Equation (25) and (26) can be written as

$$\left(\frac{\partial g}{\partial \mu} \frac{\partial \mu}{\partial \gamma^s} + \frac{\partial g}{\partial W} \right)^{-1} \frac{\partial V}{\partial \mu} \frac{\partial \mu}{\partial \gamma^s} - \lambda = 0 \quad (25')$$

and

$$\left(\frac{\partial g}{\partial \mu} \frac{\partial \mu}{\partial (\gamma^r \gamma_k^r)} + \frac{\partial g}{\partial \sigma} \frac{\partial \sigma}{\partial (\gamma^r \gamma_k^r)} + \frac{\partial g}{\partial W} \right)^{-1} \left(\frac{\partial V}{\partial \mu} \frac{\partial \mu}{\partial (\gamma^r \gamma_k^r)} + \frac{\partial V}{\partial \sigma} \frac{\partial \sigma}{\partial (\gamma^r \gamma_k^r)} \right) - \lambda = 0 \quad (26')$$

So equation (25') and (26') \Rightarrow

$$\left(\frac{\partial g}{\partial \mu} \frac{\partial \mu}{\partial \gamma^s} + \frac{\partial g}{\partial W} \right)^{-1} \frac{\partial V}{\partial \mu} \frac{\partial \mu}{\partial \gamma^s} = \left(\frac{\partial g}{\partial \mu} \frac{\partial \mu}{\partial (\gamma^r \gamma_k^r)} + \frac{\partial g}{\partial \sigma} \frac{\partial \sigma}{\partial (\gamma^r \gamma_k^r)} + \frac{\partial g}{\partial W} \right)^{-1} \left(\frac{\partial V}{\partial \mu} \frac{\partial \mu}{\partial (\gamma^r \gamma_k^r)} + \frac{\partial V}{\partial \sigma} \frac{\partial \sigma}{\partial (\gamma^r \gamma_k^r)} \right) \quad (27.1)$$

cross multiplying the inverted terms,

$$\Rightarrow \left(\frac{\partial g}{\partial \mu} \frac{\partial \mu}{\partial (\gamma^r \gamma_k^r)} + \frac{\partial g}{\partial \sigma} \frac{\partial \sigma}{\partial (\gamma^r \gamma_k^r)} + \frac{\partial g}{\partial W} \right) \frac{\partial V}{\partial \mu} \frac{\partial \mu}{\partial \gamma^s} =$$

$$\left(\frac{\partial g}{\partial \mu} \frac{\partial \mu}{\partial \gamma^s} + \frac{\partial g}{\partial W} \right) \left(\frac{\partial V}{\partial \mu} \frac{\partial \mu}{\partial (\gamma^r \gamma_k^r)} + \frac{\partial V}{\partial \sigma} \frac{\partial \sigma}{\partial (\gamma^r \gamma_k^r)} \right) \quad (27.2)$$

Since the first terms of both LHS and RHS are $\frac{dg}{d(\gamma^r \gamma_k^r)}$ and $\frac{dg}{d\gamma^s}$ respectively, so

with a little bit of manipulation, the above equation can be written as

$$\frac{dg}{d\gamma^s} \frac{\partial \mu}{\partial (\gamma^r \gamma_k^r)} - \frac{dg}{d(\gamma^r \gamma_k^r)} \frac{\partial \mu}{\partial \gamma^s} = - \frac{\frac{\partial V}{\partial \sigma} dg}{\frac{\partial V}{\partial \mu} d\gamma^s} \frac{\partial \sigma}{\partial (\gamma^r \gamma_k^r)} \quad (27.3)$$

$$\Rightarrow \left. \frac{\partial \mu}{\partial (\gamma^r \gamma_k^r)} - \frac{d\gamma^s}{d(\gamma^r \gamma_k^r)} \right|_{g(\cdot)} \frac{\partial \mu}{\partial \gamma^s} = \left. \frac{d\mu}{d\sigma} \right|_{V(\sigma, \mu)} \frac{\partial \sigma}{\partial (\gamma^r \gamma_k^r)} \quad (27.4)$$

Equation (27.4) derived above is nothing but equation (27) from the main body of the text.

QED

Proof 1.5. To get an explicit expression for γ_k^r , each element is calculated from equation (22) and (23) from the main body of the paper.

$$\frac{\partial \mu}{\partial \gamma^s} = B\gamma^s \quad (29.1)$$

$$\frac{\partial \mu}{\partial (\gamma^r \gamma_k^r)} = BE(Y_k^r) \quad (29.2)$$

$$\frac{\partial \sigma}{\partial (\gamma^r \gamma_k^r)} = \frac{\Xi + \gamma_k^r \sigma(Y_k^r)}{\sigma(Y^r)} \quad (29.3)$$

where $\Xi = \sum_{\substack{i=1 \\ i \neq k}}^n \gamma_i^r \rho_{ik} \sigma(Y_k^r) \sigma(Y_i^r)$, and where $\rho_{ij} = \frac{\text{cov}(Y_i^r, Y_j^r)}{\sigma(Y_i^r) \sigma(Y_j^r)}$. Also from equation (27),

we know

$$\frac{\partial \sigma}{\partial (\gamma^r \gamma_k^r)} = \frac{\frac{\partial \mu}{\partial (\gamma^r \gamma_k^r)} + \frac{\partial \mu}{\partial \gamma^s} \frac{d\gamma^s}{d(\gamma^r \gamma_k^r)} \Big|_{g(\cdot)}}{\frac{d\mu}{d\sigma} \Big|_{V(\cdot)}} \quad (29.4)$$

Equating (29.4) and (29.3) and substituting the values from (29.1) and (29.2) into (29.4),

we get the expression

$$B \frac{\Xi}{\sigma(Y^r)} + B \frac{\gamma_k^r \sigma^2(Y_k^r)}{\sigma(Y^r)} = \frac{BE(Y_k^r) + BY^s \frac{d\gamma^s}{d(\gamma^r \gamma_k^r)} \Big|_{g(\cdot)}}{\frac{d\mu}{d\sigma} \Big|_{V(\cdot)}} \quad (29.5)$$

canceling out the Bs and with some elementary manipulations, we get

$$\frac{\gamma_k^r \sigma^2(Y_k^r)}{\sigma(Y^r)} = \frac{E(Y_k^r) + Y^s \frac{d\gamma^s}{d(\gamma^r \gamma_k^r)} \Big|_{g(\cdot)}}{\frac{d\mu}{d\sigma} \Big|_{V(\cdot)}} - \frac{\Xi}{\sigma(Y^r)} \quad (29.6)$$

expanding the term Ξ , and with some further manipulation we get,

$$\gamma_k^r = \frac{\frac{E(Y_k^r) + Y^s \frac{dY^s}{d(Y^r \gamma_k^r)} \Big|_{g(\cdot)}}{\sigma(Y_k^r)} \frac{\sigma(Y^r)}{\sigma(Y_k^r)} - \frac{\sum_{\substack{i=1 \\ i \neq k}}^n \gamma_i^r \rho_{ik} \sigma(Y_k^r) \sigma(Y_i^r)}{\sigma^2(Y_k^r)}}{\frac{d\mu}{d\sigma} \Big|_{V(\sigma, \mu)}} \quad (29.7)$$

Equation (29.7) is the final expression as given in the paper.

QED

Appendix B. Detailed Results

The program categories are numbered as follows:

1—Feed grains	11—Other crops
2—Food grains	12—Forest and forest products
3—Oil crops	13—Soil, water, air, and climate
4—Fruits and nuts	14—Recreation
5—Vegetables	15—Technology of production
6—Cotton	16—Agriculture in society
7—Tobacco	17—Agriculture enterprise
8—Meat animal, misc. livestock and fish	18—Weeds, seeds, and bugs
9—Dairy product	19—Basic research
10—Poultry	

The years are numbered as follows:

1—1969	6—1974	11—1979	16—1984	21—1989
2—1970	7—1975	12—1980	17—1985	22—1990
3—1971	8—1976	13—1981	18—1986	23—1991
4—1972	9—1977	14—1982	19—1987	
5—1973	10—1978	15—1983	20—1988	

The K-S Test

The empirical question of concern is whether or not r_i satisfies the location and scale condition. That is, are the data a likely result from observing r_i which satisfy $r_i = \mu + \sigma x_i$, with μ being the mean and σ the standard deviation of r_i . Since x_i is a normalized variable with zero mean and constant unit variance, it is a Gaussian white noise process. And since x_i belongs to the same distribution function no matter which r_i was selected to obtain it, then all x_i from respective r_i should be a Gaussian white noise process.

To test the hypothesis that the EDFs (empirical distribution functions) of r_i do in fact differ from each other only by location and scale, all the x_i s where estimated using the observed r_i s. The Kolmogorov-Smirnov test, which is particularly useful for our purpose,

was used to find the test statistics $D = \sup[F(x_i) - G(\omega)]$, where $F(x_i)$ is the distribution function for x_i and $G(\omega)$ is a white noise process. The decision rule being, if the supremum, D , is larger than the critical value, then reject the hypothesis that the r_i s differ from each other only by μ and σ or in other words location and scale.

The test, which was conducted on several subsamples, is given below. From the test we see that all those tests for which we had taken program categories into consideration we reject the hypothesis that the r_i s differ only by LS, i.e., they do not differ by LS. However, when production years were considered, either years within a state or for all the states together, we fail to reject the hypothesis that the r_i s differs only by location and scale, i.e., the distribution for the production years considered different only by location and scale.

Test 1

Six program categories were selected nationally (all western states) and the KS test was conducted. The maximum gap gives the supremum and the critical values are given below it. The rejection rule is if the maximum gap ($D = \sup[F(x_i) - G(\omega)]$) is greater than the critical, then we reject the hypothesis that r_i s differ only by location and scale.

KS Test for Program Category 1—Feed Grains

Maximum gap = 0.6166 at frequency 0.4172

Approximate rejection limits: 1% = 0.1441, 5% = 0.1202, 10% = 0.1078.

KS Test for Program Category 2—Food Grains

Maximum gap = 0.6289 at frequency 0.6627

Approximate rejection limits: 1% = 0.1441, 5% = 0.1202, 10% = 0.1078,

KS Test for Program Category 5—Vegetables

Maximum gap = 0.4697 at frequency 1.2763

Approximate rejection limits: 1% = 0.1441, 5% = 0.1202, 10% = 0.1078.

KS Test for Program Category 15—Technology of Production

Maximum gap = 0.6727 at frequency 0.5400

Approximate rejection limits: 1% = 0.1441, 5% = 0.1202, 10% = 0.1078.

KS Test for Program Category 16—Agriculture in Society

Maximum gap = 0.6540 at frequency 0.7609

Approximate rejection limits: 1% = 0.1441, 5% = 0.1202, 10% = 0.1078.

KS Test for Program Category 18—Weeds, Seeds, and Bugs

Maximum gap = 0.5547 at frequency 0.9572

Approximate rejection limits: 1% = 0.1441, 5% = 0.1202, 10% = 0.1078.

Test 2

A particular year was used aggregated for all states and KS test was conducted, the year chosen was 1973. The results are as follows.

KS Test for the State of UT

Maximum gap = 0.1248 at frequency 0.5890

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

KS Test for the State of CO

Maximum gap = 0.1205 at frequency 0.7854

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

KS Test for the State of NV

Maximum gap = 0.1631 at frequency 2.3562

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

KS Test for the State of AZ

Maximum gap = 0.1583 at frequency 2.3562

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

KS Test for the State of MT

Maximum gap = 0.1732 at frequency 0.7854

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

KS Test for the State of KS

Maximum gap = 0.2039 at frequency 1.9635

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

KS Test for the State of OR

Maximum gap = 0.1239 at frequency 1.1781

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

KS Test for the State of NM

Maximum gap = 0.0625 at frequency 0.1963

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

KS Test for the State of CA

Maximum gap = 0.1393 at frequency 0.9817

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

KS Test for the State of ID

Maximum gap = 0.1881 at frequency 2.1598

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

Test 3

Program category 1 "Feed Crops" was used for all the states.

KS Test for UT

Maximum gap = 0.5937 at frequency 0.9817

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

KS Test for CO

Maximum gap = 0.5830 at frequency 0.7854

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

KS Test for NV

Maximum gap = 0.5355 at frequency 1.3744

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

KS Test for AZ

Maximum gap = 0.5718 at frequency 0.9817

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

KS Test for MT

Maximum gap = 0.6202 at frequency 0.7854

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

KS Test for KS

Maximum gap = 0.4450 at frequency 1.3744

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

KS Test for OR

Maximum gap = 0.5593 at frequency 0.9817

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

KS Test for NM

Maximum gap = 0.5560 at frequency 0.3927

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

KS Test for CA

Maximum gap = 0.6478 at frequency 0.9817

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

KS Test for ID

Maximum gap = 0.4314 at frequency 1.3744

Approximate rejection limits: 1% = 0.4075 5% = 0.3400 10% = 0.3050.

Test 4

For the state of Colorado years 1969, 1973, 1976, 1979, 1982, 1985, 1989, 1991 were chosen and the results were as follows.

KS Test for Series CO-1969

Maximum gap = 0.1067 at frequency 2.5525

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

KS Test for Series CO-1973

Maximum gap = 0.1205 at frequency 0.7854

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

KS Test for Series CO-1976

Maximum gap = 0.0851 at frequency 1.7671

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

KS Test for Series CO-1979

Maximum gap = 0.1104 at frequency 2.5525

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

KS Test for Series CO-1982

Maximum gap = 0.0909 at frequency 2.3562

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

KS Test for Series CO-1985

Maximum gap = 0.1529 at frequency 1.7671

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

KS Test for Series CO-1989

Maximum gap = 0.2997 at frequency 2.5525

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

KS Test for Series CO-1991

Maximum gap = 0.1091 at frequency 0.9817

Approximate rejection limits: 1% = 0.4075, 5% = 0.3400, 10% = 0.3050.

Results from the Stochastic Dominance Tests

Since the KS test indicated many regions of rejection that the distributions are in fact different from each other by only the location and scale parameter. We employ SD tests to rank the alternatives from most efficient set to least efficient one.

The data were aggregated and analyzed using stochastic dominance in six different ways to determine the absolute and relative advantage in research productivity per research dollar spent. The listings under the FSD are the prospects not dominated by FSD in successive rounds. Under SSD are those neither dominated by FSD or SSD in the successive rounds.

Under TSD are those not dominated by any of the three (FSD, SSD, TSD) in successive rounds. The results have been tabulated by each analysis.

Analysis 1: All the states were compared against each other, and the data were pooled across 19 program categories and 23 years (table B.1).

Analysis 2: Each year for all 10 states was aggregated (table B.2).

TABLE B.1

ALL-STATE COMPARISON OF 19 PROGRAM CATEGORIES AND 23 YEARS

		By FSD	By SSD	By TSD
Most efficient	A	UT, CO, NV, NM	UT, NM	UT, NM
	B	OR, ID	CO	CO
	C	AZ, MT	NV, ID	NV, ID
	D	KS	OR	OR
	E	CA	MT	MT
	F	—	AZ	AZ
	G	—	KS	KS
	H	—	CA	CA
Least efficient	H	—	CA	CA

TABLE B.2

AGGREGATION OF THE 10 STATES (YEARS NATIONAL)

		By FSD	By SSD	By TSD	
Most productive	A	1, 2, 3, 5, 6, 7, 8, 9	7, 8	7	
	B	4, 10	6, 9	8, 9	
	C	11, 13, 17, 18	5, 10	5, 6, 10	
	D	12, 14, 16, 19, 20, 21, 22, 23	1, 2, 11	1, 2, 11	
	E	15	4	4	
	F	—	3	3	
	G	—	12, 13, 17, 18	12, 13, 17, 18	
	H	—	14, 16, 22	14, 16, 22	
	I	—	15	15	
	J	—	23	23	
	K	—	21	21	
	L	—	19, 20	20	
	Least productive	M	—	—	19

Analysis 3: All the categories were aggregated across all states (table B.3).

TABLE B.3

CATEGORIES AGGREGATED ACROSS ALL STATES (PROGRAM CATEGORIES—NATIONAL)

		By FSD	By SSD	By TSD
Most efficient	A	12, 15, 18, 19	12, 15, 18, 19	12, 15, 18, 19
	B	4, 10, 14, 16, 17	16	16
	C	1, 11	4, 17	4, 17
	D	2, 8, 13	1, 10, 14	1, 10, 14
	E	5, 6	11, 13	11, 13
	F	9	2	2
	G	3, 7	8	8
	H	—	5	5
	I	—	6	6
	J	—	9	9
	Least efficient	K	—	3, 7

Analysis 4: Program categories within states. Each of the 10 states was considered to find the efficient research program categories within the state (tables B.4-B.13).

TABLE B.4

PROGRAM CATEGORIES—ARIZONA

		By FSD	By SSD	By TSD
Most efficient	A	6, 12, 15, 17, 18	15, 18	15, 18
	B	19	12, 17	12, 17
	C	14, 16	6, 19	6, 19
	D	1	14, 16	14, 16
	E	5	1	1
	F	2	5	5
	G	13	2	2
	H	3, 4, 7, 8, 9, 10, 11	13	13
	Least efficient	I	—	3, 4, 7, 8, 9, 10, 11

TABLE B.5
PROGRAM CATEGORIES—CALIFORNIA

		By FSD	By SSD	By TSD
Most efficient	A	12, 18	12	12
	B	10, 17	17, 18	17, 18
	C	15	15	15
	D	2	10	10
	E	1, 3, 4, 5, 6, 7, 9, 11, 13, 14, 16, 19	2	2
Least efficient	F	—	1, 3, 4, 5, 6, 7, 9, 11, 13, 14, 16, 19	1, 3, 4, 5, 6, 7, 9, 11, 13, 14, 16, 19

TABLE B.6
PROGRAM CATEGORIES—COLORADO

		By FSD	By SSD	By TSD
Most efficient	A	4, 12, 15, 18, 19	4, 12, 18, 19	4, 12, 18, 19
	B	1, 10, 16	1, 10, 16	1, 10, 16
	C	2	1, 16	1, 16
	D	8	2	2
	E	17	8, 10	8, 10
	F	11	17	17
	G	5, 14	11	11
	H	13	5, 14	5, 14
	I	3, 6, 7, 9	13	13
Least efficient	J	—	3, 6, 7, 9	3, 6, 7, 9

TABLE B.7
PROGRAM CATEGORIES—IDAHO

		By FSD	By SSD	By TSD
Most efficient	A	14, 15, 18	15, 18	15, 18
	C	12, 16, 17, 19	12, 14, 16, 17	12, 14, 16, 17
	D	1, 4	19	19
	E	8, 13	1	1
	F	5, 10	4, 8, 13	4, 8, 13
	G	9	5, 10	5, 10
	H	2, 3, 6, 7, 11	9	9
	Least efficient	I	—	2, 3, 6, 7, 11

TABLE B.8
PROGRAM CATEGORIES—KANSAS

		By FSD	By SSD	By TSD
Most efficient	A	15	15	15
	B	18, 19	19	19
	C	16	16, 18	16, 18
	D	17	17	17
	E	13, 11	13, 11	13, 11
	F	8	8	8
Least efficient	G	1, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12, 14	1, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12, 14	1, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12, 14

TABLE B.9
PROGRAM CATEGORIES—MONTANA

		By FSD	By SSD	By TSD
Most efficient	A	19	19	19
	B	12	12	12
	C	10, 15, 18	15	15
	D	16	18	18
	E	13, 17	10, 16	10, 16
	F	2, 4, 8	13, 17	13, 17
	G	11	4, 8	4, 8
	H	1, 3, 5, 6, 7, 9, 14	11	11
	I	—	2	2
Least efficient	J	—	1, 3, 5, 6, 7, 9, 14	1, 3, 5, 6, 7, 9, 14

TABLE B.10
PROGRAM CATEGORIES—NEW MEXICO

		By FSD	By SSD	By TSD
Most efficient	A	15	15	15
	B	14, 16, 17, 18, 19	14, 16, 17, 18, 19	14, 16, 17, 18, 19
	C	1, 10, 12, 13	10, 12, 13	10, 12, 13
	D	4, 5, 8	1	1
	E	2, 11	5, 8	5, 8
	F	6	2, 4, 11	2, 4, 11
	G	3, 7, 9	6	6
Least efficient	H	—	3, 7, 9	3, 7, 9

TABLE B.11
PROGRAM CATEGORIES—NEVADA

		By FSD	By SSD	By TSD
Most efficient	A	16, 17	16	16
	B	1, 15, 19	1, 15, 17, 19	1, 15, 17, 19
	C	8, 12, 13, 14, 18	13, 14, 18	13, 14, 18
	D	11	8, 11, 12	8, 11, 12
Least efficient	E	2, 3, 4, 5, 6, 7, 9, 10	2, 3, 4, 5, 6, 7, 9, 10	2, 3, 4, 5, 6, 7, 9, 10

TABLE B.12
PROGRAM CATEGORIES—OREGON

		By FSD	By SSD	By TSD
Most efficient	A	12	12	12
	B	15, 17	15, 17	15, 17
	C	16	16	16
	D	18, 19	18	18
	E	8	8	8
	F	13	19	19
	G	2, 10	13	13
	H	4	2, 10	2, 10
	I	14	4	4
	J	11	14	14
	K	1	11	11
	L	3, 5, 6, 7, 9	1	1
	Least efficient	M	—	3, 5, 6, 7, 9

TABLE B.13
PROGRAM CATEGORIES—UTAH

		By FSD	By SSD	By TSD
Most efficient	A	10, 18, 19	19	19
	B	12, 15, 16	12, 16, 18	12, 16, 18
	C	1, 2, 11, 14	10, 15	10, 15
	D	17	1, 2, 11, 14	1, 2, 11, 14
	E	5, 13	17	17
	F	9	13	13
	G	3, 4, 6, 7, 8	5	5
	H	—	9	9
Least efficient	I	—	3, 4, 6, 7, 8	3, 4, 6, 7, 8

Analysis 5: Most productive years within a state. Each of the 10 states was considered, to find the years, which were more productive per research dollar spent within the states (tables B.14-B.23).

TABLE B.14
MOST PRODUCTIVE YEARS PER RESEARCH DOLLAR SPENT—ARIZONA

		By FSD	By SSD	By TSD
Most efficient	A	1, 5, 6, 7, 8	1, 6, 8	1, 8
	B	2, 4	2, 7	6
	C	9	4, 5	2, 7
	D	10	9	4, 5
	E	11	10	9
	F	3	3	10
	G	15	11	13
	H	12, 13, 14, 16	15	11
	I	17, 18, 19, 20, 21, 22, 23	12, 13, 14, 16	15
	J	—	17, 18, 19, 20, 21, 22, 23	12, 13, 14, 16
	Least efficient	K	—	—

TABLE B.15

MOST PRODUCTIVE YEARS PER RESEARCH DOLLAR SPENT—CALIFORNIA

		By FSD	By SSD	By TSD
Most efficient	A	1	1	1
	B	2, 7, 8	2, 7, 8	2, 8
	C	3, 5, 9, 19	3, 9	3, 7
	D	4, 6	5, 6	9
	E	10	4	5, 6
	F	11, 12, 13, 14, 15, 16, 17	10, 19	4, 10, 19
	G	18, 20, 21, 22, 23	11, 12, 13, 14, 15, 16, 17	11, 12, 13, 14, 15, 16, 17
Least efficient	H	—	18, 20, 21, 22, 23	18, 20, 21, 22, 23

TABLE B.16

MOST PRODUCTIVE YEARS PER RESEARCH DOLLAR SPENT—COLORADO

		By FSD	By SSD	By TSD
Most efficient	A	5, 6, 7, 8	7, 8	7, 8
	B	2, 3, 4, 9, 11, 12, 13	5, 6	5, 6
	C	1, 10, 14	2, 3, 4, 9	2, 3, 4
	D	15, 16, 18, 22, 23	1, 11, 12	1, 9, 11
	E	17, 20, 21	13	12
	F	19	10, 14, 22	13
	G	—	15, 23	10, 22
	H	—	16, 21	14
	I	—	18, 20	15, 23
	J	—	17	16, 21
	K	—	19	18, 20
	L	—	—	17
	Least efficient	M	—	—

TABLE B.17

MOST PRODUCTIVE YEARS PER RESEARCH DOLLAR SPENT—IDAHO

		By FSD	By SSD	By TSD
Most efficient	A	1, 2, 7, 9, 22, 23	1, 9	1
	B	3, 6, 10, 11	2, 7	2, 7, 9
	C	5, 8, 21	10, 22, 23	10
	D	4, 12, 15	6	6, 22, 23
	E	14, 20	3, 5, 11	3, 5, 11
	F	13, 16, 17, 18, 19	8, 21	8, 21
	G	—	4, 12	4, 12
	H	—	15	15
	I	—	20	20
	J	—	14	14
	K	—	16, 17	16, 17
	L	—	13	13
	Least efficient	M	—	18, 19

TABLE B.18

MOST PRODUCTIVE YEARS PER RESEARCH DOLLAR SPENT—KANSAS

		By FSD	By SSD	By TSD
Most efficient	A	1, 2, 12	1, 12	1, 12
	B	8, 13	2, 8, 13	2, 8, 13
	C	7, 11, 14	7, 11, 14	7, 11, 14
	D	3, 5, 6, 9	3, 5, 6, 9	3, 5, 6, 9
	E	4, 10, 17	4, 10	4, 10
	F	18, 19, 20	17, 18, 19	17, 18, 19
	G	15, 16, 21, 22, 23	20	20
Least efficient	H	—	15, 16, 21, 22, 23	15, 16, 21, 22, 23

TABLE B.19

MOST PRODUCTIVE YEARS PER RESEARCH DOLLAR SPENT—MONTANA

		By FSD	By SSD	By TSD
Most efficient	A	5, 7, 8, 9, 14	8	8
	B	1, 6, 11	7	7
	C	2, 4, 10, 12	6, 9	6, 9
	D	3, 13	1, 5, 10	1, 5, 10
	E	15, 16	2, 11	2, 11
	F	17, 18, 19, 20, 21, 22, 23	4, 12	4, 12
	G	—	3, 13, 14	3, 13, 14
	H	—	15, 16	15, 16
	Least efficient	I	—	17, 18, 19, 20, 21, 22, 23

TABLE B.20

MOST PRODUCTIVE YEARS PER RESEARCH DOLLAR SPENT—NEW MEXICO

		By FSD	By SSD	By TSD
Most efficient	A	1, 5, 6, 7, 9	1, 5, 6, 7, 9	1, 6, 7, 9
	B	2, 3, 4, 8, 11	2, 4, 8, 11	4, 5, 11
	C	10	3, 10	2, 8
	D	12, 16, 17, 18	12, 16, 17, 18	3, 10
	E	13, 14, 15, 22	13, 14, 22	12, 16, 17, 18
	F	19, 20, 21, 23	15, 23	13, 14, 22
	G	—	21	15, 22
	H	—	20	21
	I	—	19	20
	Least efficient	J	—	—

TABLE B.21

MOST PRODUCTIVE YEARS PER RESEARCH DOLLAR SPENT—NEVADA

		By FSD	By SSD	By TSD
Most efficient	A	1, 7, 8, 9, 11	7, 8	8
	B	6, 10	6, 9	7, 9
	C	2, 5, 22, 23	1, 10, 11	1, 6
	D	3, 12	2	10, 11
	E	13, 14, 15	3, 5	2
	F	20, 21	22, 23	3, 5
	G	18	12	22, 23
	H	4, 16, 17, 19	13, 14, 15	12
	I	—	20	13, 14, 15
	J	—	21	20
	K	—	18	21
	L	—	4, 16, 17, 19	18
	Least efficient	M	—	—

TABLE B.22

MOST PRODUCTIVE YEARS PER RESEARCH DOLLAR SPENT—OREGON

		By FSD	By SSD	By TSD
Most efficient	A	1, 7, 8, 13, 18	7, 8, 18	7, 8
	B	5, 6, 9, 17	6, 9, 17	6, 9, 18
	C	10, 11, 15, 19, 20	10, 13	10, 13, 17
	D	2, 12, 14, 16	1, 5, 11, 15, 19	1, 5, 11, 15, 19
	E	4	2, 14, 16, 20	2, 14, 16, 20
	F	3	12	12
	G	21, 22	4	4
	H	23	3	3
	I	—	21, 22	21, 22
	Least efficient	J	—	23

TABLE B.23

MOST PRODUCTIVE YEARS PER RESEARCH DOLLAR SPENT—UTAH

		By FSD	By SSD	By TSD
Most efficient	A	5, 6, 7, 8, 18	6, 7, 8	7, 8
	B	4, 9, 10, 11, 12, 16, 19, 20	5	5
	C	1, 2, 17, 21, 22, 23	9, 10, 11, 12	9, 11, 12
	D	3, 13, 15	2, 4, 18, 19	2, 4, 10
	E	14	1, 16, 17, 20	1, 18, 20
	F	—	21, 22, 23	16, 17, 19
	G	—	3, 13, 15	22, 23
	H	—	14	21
	I	—	—	3, 13, 15
	Least efficient	J	—	—

Analysis 6: Most productive state(s) across all years and research program categories.

In this analysis, the states are numbered as follows: 1—Utah, 2—Colorado, 3—Nevada, 4—Arizona, 5—Montana, 6—Kansas, 7—Oregon, 8—New Mexico, 9—California, and 10—Idaho (see tables B.24-B.41).

TABLE B.24

MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM
CATEGORY 1—FEED GRAINS

		By FSD	By SSD	By TSD
Most efficient	A	1, 8	1	1
	B	2	2, 8	2, 8
	C	3	3	3
	D	10	10	10
	E	4	4	4
	F	7	7	7
Least efficient	G	5, 6, 9	5, 6, 9	5, 6, 9

TABLE B.25

MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM
CATEGORY 2—FOOD GRAINS

		By FSD	By SSD	By TSD
Most efficient	A	1, 2, 8	1	1
	B	5	2, 8	2, 8
	C	4, 7	5	5
	D	9	4, 7	4, 7
	E	3, 6, 10	9	9
Least efficient	F	—	3, 6, 10	3, 6, 10

TABLE B.26

MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM
CATEGORY 3—OIL CROPS

		By FSD	By SSD	By TSD
Most efficient	A	2	2	2
	B	8	8	8
	C	5, 10	5, 10	5, 10
	D	7	7	7
Least efficient	E	1, 4, 6, 9	1, 4, 6, 9	1, 4, 6, 9

TABLE B.27

MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM
CATEGORY 4—FRUITS & NUTS*

	By FSD	By SSD	By TSD
Most and least efficient	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	1, 2, 3, 4, 5, 6, 7, 8, 9, 10

*For fruits and nuts, there is no comparative advantage of any SAES. The most efficient and the least efficient sets are the same.

TABLE B.28

MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM
CATEGORY 5—VEGETABLES

		By FSD	By SSD	By TSD
Most efficient	A	8	8	8
	B	2	2	2
	C	1	1	1
	D	4	4	4
	E	10	10	10
Least efficient	F	3, 5, 6, 7, 9	3, 5, 6, 7, 9	3, 5, 6, 7, 9

TABLE B.29

MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM
CATEGORY 7—TOBACCO*

		By FSD	By SSD	By TSD
Most and least efficient		1, 2, 3, 4, 5, 6, 7, 8, 9, 10	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	1, 2, 3, 4, 5, 6, 7, 8, 9, 10

*For tobacco, there is no comparative advantage of any SAES. The most efficient and the least efficient sets are the same.

TABLE B.30

MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM
CATEGORY 8—MEAT ANIMAL, MISCELLANEOUS LIVESTOCK, AND FISH

		By FSD	By SSD	By TSD
Most efficient	A	2, 3, 8	2, 3, 8	2, 3, 8
	B	7	7	7
	C	5, 10	5, 10	5, 10
	D	6	6	6
Least efficient	E	1, 4, 9	1, 4, 9	1, 4, 9

TABLE B.31

MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM
CATEGORY 9—DAIRY PRODUCTS

		By FSD	By SSD	By TSD
Most efficient	A	1	1	1
	B	10	10	10
Least efficient	C	2, 3, 4, 5, 6, 7, 8, 9	2, 3, 4, 5, 6, 7, 8, 9	2, 3, 4, 5, 6, 7, 8, 9

TABLE B.32

MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM
CATEGORY 10—POULTRY

		By FSD	By SSD	By TSD
Most efficient	A	1, 8	1, 8	1, 8
	B	2, 5	2, 5	2, 5
	C	7, 9	7, 9	7, 9
	D	10	10	10
Least efficient	E	3, 4, 6	3, 4, 6	3, 4, 6

TABLE B.33

MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM
CATEGORY 11—OTHER CROPS

		By FSD	By SSD	By TSD
Most efficient	A	1, 3	1	1
	B	2, 8	3, 8	3, 8
	C	5, 6	2	2
	D	7	5, 6	5, 6
	E	4, 9, 10	7	7
Least efficient	F	—	4, 9, 10	4, 9, 10

TABLE B.34

MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM
CATEGORY 12—FOREST & FOREST PRODUCTS

		By FSD	By SSD	By TSD
Most efficient	A	7	7	7
	B	2	2	2
	C	1, 8	1	1
	D	9, 10	8, 9	8, 9
	E	4, 5	10	10
	F	3	4, 5	5
	G	6	3	4
	H	—	6	3
	I	—	—	6
Least efficient				

TABLE B.35

MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM
CATEGORY 13—SOIL, WATER, AIR, & CLIMATE

		By FSD	By SSD	By TSD
Most efficient	A	8	8	8
	B	3, 10	3	3
	C	5	5	5
	D	1, 7	1	1
	E	6	7	7
	F	2	10	10
	G	4	6	6
	H	9	2	2
	I	—	4	4
	J	—	9	9
Least efficient				

TABLE B.36

MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM
CATEGORY 14—RECREATION

		By FSD	By SSD	By TSD
Most efficient	A	8, 10	8	8
	B	1	1, 10	1, 10
	C	3	3	3
	D	2, 4	4	4
	E	7	2	2
	F	5, 6, 9	7	7
Least efficient	G	—	5, 6, 9	5, 6, 9

TABLE B.37

MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM
CATEGORY 15—TECHNOLOGY OF PRODUCTION

		By FSD	By SSD	By TSD
Most efficient	A	8	8	8
	B	1, 2, 10	1, 2, 10	1, 2, 10
	C	3, 6	6	6
	D	4	3, 4	3, 4
	E	5, 7	7	7
	F	9	5	5
Least efficient	G	—	9	9

TABLE B.38

MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM
CATEGORY 16—AGRICULTURE IN SOCIETY

		By FSD	By SSD	By TSD
Most efficient	A	1, 3, 8	1, 3, 8	1, 3, 8
	B	2, 10	2, 10	2, 10
	C	6, 7	6, 7	6, 7
	D	5	5	5
	E	4	4	4
Least efficient	F	9	9	9

TABLE B.39

MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM
CATEGORY 17—AGRICULTURE ENTERPRISE

		By FSD	By SSD	By TSD
Most efficient	A	3, 8, 10	3, 8	3, 8
	B	1, 7	1, 7, 10	1, 7, 10
	C	4	4	4
	D	2	2	2
	E	5, 6	5, 6	5, 6
Least efficient	F	9	9	9

TABLE B.40

MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM
CATEGORY 18—WEEDS, SEEDS, & BUGS

		By FSD	By SSD	By TSD
Most efficient	A	1	1	1
	B	2	2	2
	C	3, 8, 10	8, 10	8, 10
	D	4, 5, 6	3, 4	3, 4
	E	7, 9	5	5
	F	—	6, 7	6, 7
Least efficient	G	—	9	9

TABLE B.41

MOST PRODUCTIVE STATES ACROSS ALL YEARS AND RESEARCH PROGRAM
CATEGORY 19—BASIC RESEARCH

		By FSD	By SSD	By TSD
Most efficient	A	1	1	1
	B	2, 3, 5, 8	2, 3	2, 3
	C	6, 10	5, 8	5, 8
	D	4, 7	6, 10	6, 10
	E	9	4, 7	4, 7
Least efficient	F	—	9	9

Appendix C. Data

		RESEARCH CATEGORY DATA																							
UTAH	years	1968	1970	1971	1972	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	
	categories																								
1		0.029452	0.015989	0.0134	0.019691	0.018554	0.02127	0.044581	0.048312	0.043953	0.029996	0.01776	0.011332	0.002581	0.001463	0.001949	0.001987	0.002357	0.002827	0.001511	0.001649	0.001741	0.002515	0.01730	0.004459
2		0	0.002265	0.002926	0.002265	0.002265	0.002265	0.002265	0.002265	0.002265	0.002265	0.002265	0.002265	0.002265	0.002265	0.002265	0.002265	0.002265	0.002265	0.002265	0.002265	0.002265	0.002265	0.002265	0.002265
3		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6		0	0.003186	0.003186	0.00074	0.002356	0.010076	0.007734	0.007734	0.007734	0.007734	0.007734	0.007734	0.007734	0.007734	0.007734	0.007734	0.007734	0.007734	0.007734	0.007734	0.007734	0.007734	0.007734	0.007734
7		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9		0	0.002054	0	0.000611	0.001919	0.002994	0.003143	0.003344	0.003996	0.002352	0.001137	0.000429	0.000035	0.000099	0.000478	0.000163	0.000267	0.000348	0.000348	0.000348	0.000348	0.000348	0.000348	0.000348
10		0.002881	0.002881	0	0.001622	0.007464	0.007464	0.006851	0.004589	0.005185	0.002638	0.001555	0.002163	0.001444	0.000569	0.000661	0.001405	0.002121	0.003337	0.002121	0.003337	0.002121	0.003337	0.002121	0.003337
11		0	0	0.442395	0.666494	0.739574	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12		0.000477	0.000477	0.002351	0.002351	0.002351	0.002351	0.002351	0.002351	0.002351	0.002351	0.002351	0.002351	0.002351	0.002351	0.002351	0.002351	0.002351	0.002351	0.002351	0.002351	0.002351	0.002351	0.002351	0.002351
13		0	0.00976	0.00976	0.012063	0.002971	0.037481	0.034944	0.019136	0.006552	0.015398	0.002926	0.023983	0.018187	0.004246	0	0	0	0	0	0	0	0	0	0
14		0.001964	0.001964	0.002574	0.003636	0.006481	0.006033	0.006101	0.004811	0.004653	0.002178	0.006966	0.006436	0.004541	0.004452	0.002930	0.006736	0.003366	0.002930	0.006736	0.003366	0.002930	0.006736	0.003366	0.002930
15		0.004889	0.004889	0	0.015508	0.03480	0.046423	0.046318	0.017974	0.015953	0.014077	0.014077	0.014077	0.014077	0.014077	0.014077	0.014077	0.014077	0.014077	0.014077	0.014077	0.014077	0.014077	0.014077	0.014077
16		0	0.015126	0.013426	0.018118	0.008114	0.196565	0.066001	0.066001	0.018157	0.0274	0.009135	0.006955	0.002766	0.003166	0.003654	0.004414	0.006071	0.005974	0.010474	0.007159	0.004174	0.005651	0.007465	0.007465
17		0.006654	0.006654	0.005127	0.005127	0.005127	0.005127	0.005127	0.005127	0.005127	0.005127	0.005127	0.005127	0.005127	0.005127	0.005127	0.005127	0.005127	0.005127	0.005127	0.005127	0.005127	0.005127	0.005127	0.005127
18		0.004180	0.004180	0.004180	0.004180	0.004180	0.004180	0.004180	0.004180	0.004180	0.004180	0.004180	0.004180	0.004180	0.004180	0.004180	0.004180	0.004180	0.004180	0.004180	0.004180	0.004180	0.004180	0.004180	0.004180
19		0	0.01264	0.01264	0.027255	0.047173	0.123159	0.176526	0.499349	0.431189	0.181659	0.072411	0.009964	0	0.02081	0.022813	0.017338	0.007861	0.160233	0.003818	0.319174	0.022334	0.015448	0.012174	0.012174
20		0	0.007799	0.007799	0.043399	0.31156	0.613356	0.577164	0.357157	0.117033	0.455538	0.134511	0.058607	0.05706	0.003749	0.068248	0.015338	0.10918	0.17828	0.10918	0.002421	0.003175	0.02268	0.009950	0.009950

		RESEARCH CATEGORY DATA																							
COLORADO	years	1968	1970	1971	1972	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	
	categories																								
1		0.000695	0.001863	0.013127	0.014542	0.013127	0.030006	0.047735	0.02408	0.016169	0.006726	0.006962	0.006852	0.004415	0.002772	0.001233	0.004023	0	0	0	0.002225	0.004039	0.006139	0.006181	0.006181
2		0.005092	0.003078	0.003783	0.007263	0.002131	0.030859	0.066191	0.032139	0.021431	0.006163	0.003938	0.004144	0.001722	0	0.001308	0.002952	0.002952	0.001123	0	0	0.000375	0.000375	0	0
3		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4		0	0	0	0.274481	0.30461	0.748841	0.702177	0.519051	0.286726	0.033803	0.015204	0.021306	0.029944	0.019179	0.019688	0.009649	0	0	0	0	0	0.002869	0.002869	0.002869
5		0	0	0	0.009052	0.001863	0.011168	0.013524	0.009684	0.003855	0.002222	0.002071	0.003146	0.001421	0.002209	0.001969	0.003761	0.002633	0.002924	0	0	0	0	0	0
6		0	0	0	0	0	0.002111	0.002111	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8		0.004119	0.003448	0.009746	0.010397	0.020065	0.031003	0.040006	0.015543	0.006946	0.000006	0.001733	0.002860	0.000778	0.004511	0.003709	0.000977	0.000017	0.000028	0.000191	0.000008	0.000713	0.001708	0.001708	0.000676
9		0.000818	0	0	0	0	0	0.000716	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10		0.003011	0.003011	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.001135	0.001547	0.001547	0.001547	0.001547
11		0.001731	0.001731	0.002688	0.004498	0.010848	0.018116	0.023090	0.008504	0.004949	0.000961	0.001748	0.002411	0.001521	0.001269	0.000606	0.000606	0	0	0	0	0	0	0	0
12		0.002605	0.002605	0.040088	0.002605	0.002605	0.051354	0.049179	0.013493	0.054462	0.001015	0.001015	0.001015	0.001015	0.001015	0.001015	0.001015	0.001015	0.001015	0.001015	0.001015	0.001015	0.001015	0.001015	0.001015
13		0.007193	0.002778	0.002109	0.001598	0.001781	0.002275	0.006177	0.000029	0.000051	0.001513	0.001613	0.001613	0.001613	0.001613	0.001613	0.001613	0.001613	0.001613	0.001613	0.001613	0.001613	0.001613	0.001613	0.001613
14		0	0.012927	0.013071	0.013262	0.013453	0.013644	0.013835	0.014026	0.014217	0.014408	0.014600	0.014791	0.014982	0.015173	0.015364	0.015555	0.015746	0.015937	0.016128	0.016319	0.016510	0.016701	0.016892	0.017083
15		0.014181	0.042013	0.005235	0.010747	0.005025	0.009613	0.247489	0.211915	0.033115	0.014841	0.010782	0.008195	0.004356	0.003406	0.005134	0.003724	0.003887	0	0	0.001465	0.001465	0.002504	0.000004	0.000004
16		0.00468	0.00468	0.00468	0.00468	0.00468	0.00468	0.00468	0.00468	0.00468	0.00468	0.00468	0.00468	0.00468	0.00468	0.00468	0.00468	0.00468	0.00468	0.00468	0.00468	0.00468	0.00468	0.00468	0.00468
17		0.022526	0.022526	0.022526	0.022526	0.022526	0.022526	0.022526	0.022526	0.022526	0.022526	0.022526	0.022526	0.022526	0.022526	0.022526	0.022526	0.022526	0.022526	0.022526	0.022526	0.022526	0.022526	0.022526	0.022526
18		0	0.023168	0.023168	0.019784	0.014249	0.374447	0.413871	0.181661	0.057169	0.009603	0.135711	0.431334	0.104492	0.009578	0.052871	0.016664	0.004502	0	0	0	0.002876	0.004502	0.002876	0.002876
19		0	0.008981	0.002001	0.006623	0.130772	0.189984	0.266161	0.174582	0.109873	0.011623	0.026213	0.003648	0.004743	0.017653	0.015241	0.000006	0.005211	0.000394	0.009311	0.000869	0.004466	0.004471	0.003001	0.003001

(DAHO)	years	1969	1970	1971	1972	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	
	categories																								
	1	0.016378	0.015441	0.008718	0	0.004513	0.007896	0.008802	0.004269	0.000654	0	0	0	0.000639	0.000639	0.000639	0.001483	0.00189	0.001189	0.001122	0.002522	0.002522	0.002522	0.002522	
	2	0.002848	0.001737	0.001717	0.001562	0.001562	0	0	0	0	0.000664	0.000664	0.000664	0	0	0	0.000255	0.00079	0.00079	0.00079	0.001153	0.001153	0.001153	0.001153	
	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	5	0.005198	0.002351	0	0	0.023451	0.000681	0.000681	0.000681	0.000681	0.002521	0.002521	0.002521	0.000639	0.000639	0.000639	0	0.000639	0.000639	0.000639	0.000639	0.000639	0.000639	0.000639	
	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	8	0.000951	0.000486	0.003946	0.0038	0.000631	0.000434	0.000422	0.000731	0.004495	0.003634	0.004816	0.003379	0.002714	0.002131	0.001389	0	0	0	0	0	0	0.000442	0.000442	0.000442
	9	0.009194	0.002483	0.001122	0	0.001426	0.001426	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.000311	0.000311	0.000311
	10	0.022277	0.022277	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	11	0.004292	0.002822	0	0	0.000091	0.004213	0.004213	0.003512	0.003513	0.000725	0.000374	0.000066	0.000289	0.000289	0.000289	0	0	0	0	0	0	0	0	
	12	0	0	0	0	0	0	0.010063	0.010063	0.010063	0	0	0	0	0.010063	0.010063	0.010063	0.010063	0.010063	0.010063	0.010063	0.010063	0.010063	0.010063	
	13	0.000657	0.000657	0	0	0	0.000769	0.000699	0.015029	0.014371	0.000698	0.003394	0.001634	0.00202	0.001703	0.000641	0	0	0	0.000772	0.000412	0.000412	0.001166	0.001166	
	14	0	0	0	0	0	0.062122	0.062122	0.062122	0.062122	0.062122	0.062122	0.062122	0.062122	0.062122	0.062122	0.062122	0.062122	0.062122	0.062122	0.062122	0.062122	0.062122	0.062122	
	15	0.183959	0.111745	0.014223	0	0.000528	0.010261	0.024278	0.034685	0.034685	0.028209	0.010774	0.004409	0.001617	0	0	0	0	0	0.011508	0.02021	0.02129	0.00389	0.00389	
	16	0.004461	0.009986	0	0	0.011762	0.011762	0.011762	0.014620	0.02344	0.011944	0.005144	0.009503	0.004423	0.000666	0.005545	0.002929	0.0008	0	0	0	0.00294	0.004011	0.004011	
	17	0.000819	0.004682	0	0	0.000478	0.000478	0.000478	0.000478	0.000478	0.000478	0.000478	0.000478	0.000478	0.000478	0.000478	0.000478	0.000478	0.000478	0.000478	0.000478	0.000478	0.000478	0.000478	
	18	0	0.001181	0.007074	0.006207	0.007436	0.185217	0.209692	0.134318	0.043451	0.004522	0.004522	0.002183	0	0	0	0	0	0	0.000282	0.000302	0.000302	0.000302	0.000302	
	19	0	0.000044	0.010054	0.010054	0.010054	0.010054	0.010054	0.010054	0.010054	0.010054	0.010054	0.010054	0.010054	0.010054	0.010054	0.010054	0.010054	0.010054	0.010054	0.010054	0.010054	0.010054	0.010054	