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ECONOMIC ANALYSIS OF COTTON INTEGRATED PEST MANAGEMENT STRATEGIES: A COMMENT

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In the July 1983 edition of the Southern Journal of Agricultural Economics, Liapis and Moffitt evaluated several pest management strategies with respect to risk using the exponential-utility, moment-generating function (EUMGF) approach to stochastic efficiency. The Liapis/Moffitt study makes economic comparisons of four integrated pest management (IPM) strategies for control of Heliothis (bollworm and tobacco budworm) around Portland, Arkansas. The purpose of this comment is to reconsider the conclusions from their economic model. Specifically, this discussion presents the following criticisms: (1) the theoretical limitations of single-valued utility functions, (2) the problems in the estimation of the probability distributions, and (3) the faulty predictions based on the analysis.

THEORETICAL LIMITATIONS OF THE EUMGF

The limitation of the EUMGF approach as with any single-valued utility function is the chance that it does not accurately reflect preferences. Researchers have continued to use single-valued utility functions because efficiency criteria, such as stochastic dominance, have difficulty in providing complete rankings of alternatives. However, stochastic dominance techniques are becoming more commonly selected over single-valued utility functions.

The EUMGF approach assumes that producer preferences can be represented by a negative exponential utility function. The authors justify the use of this approach for several reasons. First, the negative exponential utility function reflects a constant degree of risk aversion unlike quadratic utility func-

tions which imply increasing absolute risk aversion. Second, this approach easily accommodates different specifications of the profit distribution for each pest management strategy. Finally, they note this approach will identify a unique efficient strategy under risk. Stochastic dominance may not provide a complete ranking of alternatives since it imposes fewer restrictions of the form of the utility function than the EUMGF approach.

These advantages still do not overcome a major limitation of single-valued utility funcitons. While the EUMGF approach avoids the arduous task of the direct elicitation of the utility function and the biases therein (Young, p. 1,064), the utility function is an exact representation of preferences and a misspecification of this function will produce an inaccurate ordering of the producer preferences. Musser et al. provide additional evidence on the problems of specifying singlevalued utility functions; they discovered that different functional forms could result in different preference classifications; even when based on the same data. The problem can be viewed in terms of hypothesis testing. As such, single-valued utility functions have a high probability of Type I errors, the rejection of the null hypothesis that the expected utility of one alternative is equal to the expected utility of another alternative when it is actually true. Basing the ranking of alternatives on the differences between expected utilities, misspecification could lead to the elimination of a preferred alternative from the efficient set.

Unlike the EUMGF approach, stochastic dominance does not require explicit knowledge of a producer's utility functions but only certain general characteristics. The problem with stochastic dominance, as the

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authors indicate, is its generality. It does not provide enough information on which to rank alternatives under risk. In terms of a hypothesis test, the stochastic dominance criteria have a higher probability of Type II errors, the acceptance of the null hypothesis that the expected utility of one alternative is equal to the expected utility of another alternative when it is false. These criteria may fail to eliminate many alternatives from the efficient set. Thus, the Type II error may be large. Stochastic Dominance With Respect to a Function, SDWRF, provides a flexibility to trade Type I and Type II errors by determining the degree of precision with which risk preferences are measured (Meyer; King and Robison). In addition, SDWRF avoids the necessity of specifying a form of the probability distribution by using an empirical distribution, as recommended by Pope and Ziemer.

In comparing the EUMGF approach and the stochastic dominance criteria, there is a tradeoff between the degree of accuracy and the discriminatory power of each method of preference measurement (King and Robison, p. 518.). The researcher must realize the degree of precision of the utility measure will affect both Type I and Type II errors. While the EUMGF approach has a high probability of a Type I error and a low probability of a Type II error, the stochastic dominance criteria have, in general, a high probability of Type II error and a low probability of Type I error. In selecting the EUMGF approach, the authors apparently were more concerned with avoiding Type II errors at the risk of making Type I errors. It can be argued that Type I errors (inaccurate rankings) may be much more costly that Type II errors (incomplete rankings).

ESTIMATION OF THE PROBABILITY DISTRIBUTIONS

An important component of the EUMGF approach is the estimation of the probability distributions of net returns. Several questions arise concerning the appropriateness of the probability distributions for the Liapis/Moffitt analysis. First, the estimation of these distributions are based on a single year of cross-sectional data. However, the variation in data exhibited across farms at a given time can be different from the variation exhibited by farms for successive time periods. Thus, the authors ignored possible temporal variation which can be greater than cross-sectional

variation. A review of historical records shows there are yield differences through time between Ashley and Chicot counties in Southeast Arkansas, the areas in the community pest control strategy (T2) (Scott, p. 62). Such differences cannot be controlled in cross-sectional analysis.

The probability distributions are estimated with only yield and pest management costs as the random variables. In the Liapis/Moffitt EUMGF approach, the cotton price received by farmers is fixed rather than random. This neutralizes the uncertainty associated with the output price and may give an unrealistic estimate of the distributions. This simplification may be, perhaps once again, a function of a single year of cross-sectional data. Furthermore, it is a common observation that price uncertainty may result in increased use of risk reducing inputs (Farnsworth and Moffitt), which pest management practices are expected to be.

Other random influences not considered in the estimation are the existence of free riders and the intensity of insect pressure. These influences can have a tremendous impact on the estimated distributions for the community strategy (T2), the untreated fields inside the community strategy (T3), and the untreated fields outside the community strategy (T4). Presence of free riders distorts the cost data for not only the untreated strategies T3 and T4, but also for the community control. How much of an impact free riders have on estimating the probability distributions in the long run will depend upon the intensity of the insect pressure for that year. If the insect pressure is heavy, the community strategy can tolerate internal free riders but its effectiveness is reduced. The free riders, by not spraying with the rest of the community, can disrupt the management of the pest population as a group. During a light infestation year, the effectiveness of the community concept strategy is not lessened but over time the integrity of the community is threatened. In fact, 1981 was not a serious year for He*liothis* in the Portland region (J. R. Phillips, personal communication). The incentive to 'free ride' is stronger for that year since the pest population was not overly threatening. Given these impacts, it seems that strategies T3 and T4 are not viable options available to growers in the long run.

ERRORS IN PREDICTION

The Liapis/Moffitt model's prediction is faulty (Type I error). While the authors se-

lected the Trichogramma strategy (T1) as the preferred one, its benefits were seriously questioned and the program terminated after 1982 due to difficulties encountered in a season with heavy boll weevil pressure (J. R. Phillips, personal communication). By contrast, preference of the community strategy (T2) is indicated by the fact it has spread to six other areas in Southeast Arkansas and now includes almost 150,000 acres.

CONCLUSION

This comment shows the limits of applying the single-valued utility function to the rank-

ing of new technology such as IPM under risk. Given the dynamics of the community control strategy, the random influences on the estimation of the probability distributions, and the faulty predictions of the EUMGF model, single-valued utility functions fail to properly compare IPM strategies under risk. Imposition of a specific, precise functional form for utility runs a high probability for misrepresenting preferences, resulting in a Type I error. Caution must also be exercised when using 1-year of cross-sectional data that may not represent all relevant sources of uncertainty.

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