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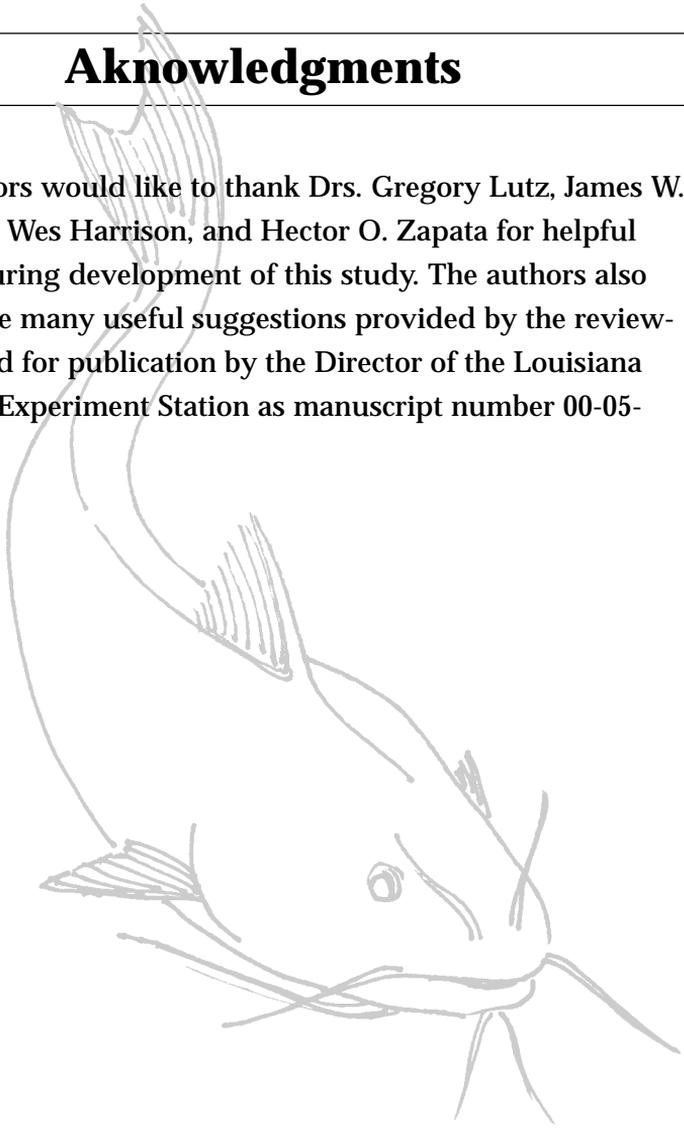
The Impact of Price and Yield Variability on Southeastern U.S. Catfish Producer Operations

Richard F. Kazmierczak Jr. and Patricia Soto



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Richard F. Kazmierczak Jr. and Patricia Soto¹

Introduction

The commercial production of catfish in the United States has increased at a phenomenal rate in the last three decades (Figure 1). By 1997, channel catfish culture was the largest aquaculture industry in the United States, with catfish production representing 72 percent (by weight) and 55 percent (by value) of the entire industry (U.S. Joint Subcommittee on Aquaculture 1999). Most of this production was located in the southeastern United States. Of the total 1999 production surface area (175,220 acres), 94 percent was located in Mississippi (105,000 acres), Arkansas (25,500 acres), Alabama (21,300 acres), and Louisiana (16,600 acres) (National Agricultural Statistics Service 1999).

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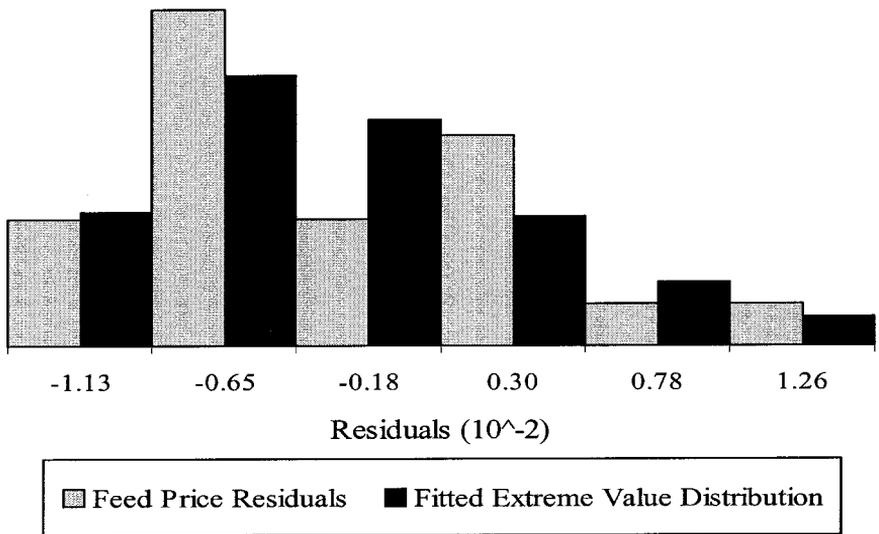


Figure 1. Total catfish production (measured as round weight processed) in the United States (thousand pounds), 1970-1999. Source: National Agricultural Statistics Service (NASS), Agricultural Statistics Board, U.S. Department of Agriculture.

Along with changes in output, catfish production has undergone structural changes as farms adjusted to the income and resource problems that commonly emerge in new industries. Farm numbers declined as producers left the industry, and those remaining mechanized, modernized, and grew in size (Figure 2). Nonetheless, most catfish farms in the southeastern United States still have small, noncorporate structures that limit opportunities for enterprise diversification and concentrate risk among individual producers and their families. Because catfish producers have little ability to influence input or output prices, and may actually be selling into oligopsony markets (Kinnucan & Sullivan 1986; Kouka 1995), their ability to manage risk is often severely tested.

The sources of risk affecting catfish aquaculture are numerous, ranging from weather fluctuations and bird predation to the greater agricultural and regulatory policy-making processes. If

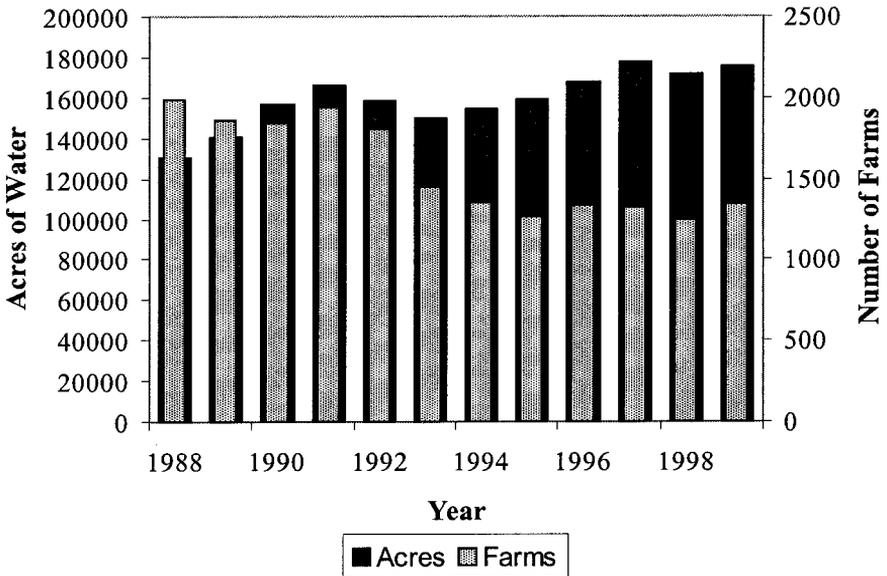


Figure 2. Number of catfish operations and water surface acres used for catfish production in the United States, 1988-1999.
Source: National Agricultural Statistics Service (NASS), Agricultural Statistics Board, U.S. Department of Agriculture.

ignored in a producer's decision making, each source of risk has the potential to affect enterprise operation and profitability adversely. But, to successfully incorporate risk into decision making, producers need information about risk and a way of measuring the actual risk that needs to be accounted for when planning farm operations. The problem for catfish producers is that their industry is relatively new, and information about price and yield risk is meager (Cacho et al. 1986). Hatch et al. (1989) investigated aquaculture yield uncertainty, but this research was targeted specifically at the impacts on Alabama producers. Further review of the literature has failed to identify any other significant studies detailing the influence of price and yield risk on aquaculture production. To fill this important knowledge gap, this study empirically assessed the impact of stochastic price and yield variables on catfish producer profits within a risk-evaluation framework.

Risk and Decision Making

Popular usage of the term risk implies almost no difference between risk and uncertainty, although Knight (1921) and subsequent researchers suggested a distinction between the concepts. Knight proposed that if a particular situation is similar to others that had occurred in the past, and information about the outcomes of previous choices could be used in the formation of a probability density function for the outcome of a choice in the present situation, then the situation is risky. However, if the situation is unique, so that no information from similar situations in the past is available, the situation is uncertain. Knight associated objective probabilities with risk and subjective probabilities with uncertainty.

Objective probabilities are defined as the relative frequency of an event's occurrence in a large set of observations. In the case of economic processes, objective probabilities are based on historical time series data. Subjective probabilities are beliefs held by decision makers that reflect their degree of uncertainty about some idea, event, or proposition. This type of probability cannot be computed directly from historical data, but decision makers may use historical probabilities to help formulate their subjective probabilities (Young et al. 1979). Modern decision theory presumes that decision makers do not totally rely on either objective or subjective probabilities. Rather, decision makers form subjective probabilities based on logical deductions, on inferences from historical data, on intuition, or on any combination of these three types of information (King 1979). From this perspective, the terms risk and uncertainty can be used interchangeably.

An analysis of risk depends, to some extent, on the conceptual framework used to define the decision-making process. Given an appropriate framework, producer attitudes toward risk and the probabilities they assign to future events can be used to explain why producers often make different decisions under similar situations. Theoretically, a decision maker's attitude toward risk can be inferred from the shape of his or her utility function, with the attitudes varying depending on the psychological makeup of the risk taker and the probable outcome of events (Robison et al. 1984). The empirical problem is that imprecise

measurement of decision maker preferences can lead to incorrect derivation of the utility function. Because a utility function, once estimated, is usually treated as an exact representation of preferences when alternative choices are ordered, inaccuracies may imply the rejection of a choice actually preferred by the decision maker. To overcome these problems, researchers have developed techniques for ordering risky prospects that do not require the full specification of the utility function. These techniques are often termed risk efficiency analyses.

A number of risk efficiency criteria have been developed, including mean-variance efficiency (EV), mean-absolute deviation efficiency, target MOTAD, first-degree stochastic dominance, second-degree stochastic dominance, and stochastic dominance with respect to a function. These techniques divide the decision alternatives into two mutually exclusive sets, an efficient set and an inefficient set (Levy & Sarnat 1972). The efficient set contains the preferred choice of every individual whose preferences conform to the restrictions associated with the criteria (King & Robison 1981). Thus, the inefficient set contains alternatives that, if chosen, would unambiguously lower expected utility. Of the available criteria, many researchers prefer stochastic dominance efficiency because of its potential ability to consider various facets of a distribution.

First degree stochastic dominance (FSD) (Hadar & Russell 1969; Hanoch & Levy 1969) assumes decision makers prefer more to less or that they have a positive marginal utility of income. Since the FSD criterion holds for all decision makers who prefer more to less, its use is limited because a large number of distributions may intersect for any given application of the FSD. In other words, given that FSD criterion places so few restrictions on the utility function, it often eliminates few choices from consideration and thus has low discriminatory power. Second degree stochastic dominance (SSD) is more discriminating than FSD because it assumes that decision makers are risk averse (positive but decreasing utility of income). Under SSD, distributions are compared based on the cumulative area under the distributions. Stochastic dominance with respect to a function (SDRF) is even more discriminating because it orders uncertain choices for decision makers whose absolute risk aversion functions lie within specified lower and upper bounds (Meyers 1977). However, SDRF



requires specific information on the lower and upper bounds of producer risk aversion. This information can be measured or approximated (King & Robison 1981), but it is time consuming and subject to numerous biases.



Data and Empirical Methods

Like most economic studies, the present research relied on nonexperimental data in which the underlying conditions are not subject to control and cannot be replicated. Nonexperimental data can lead to various empirical problems, including multicollinearity, autocorrelation, and heteroskedasticity. For example, to the extent that the stochastic disturbance term represents conditions relevant to the model but not accounted for explicitly, autocorrelation will manifest itself in a dependence of the stochastic disturbance term in one period on that in another. These empirical issues are examined later. The first part of this section focuses on the sources and nature of the data used in the study.

Yield Data

Estimated catfish yields have not been systematically measured by statistical reporting agencies, and some of the information needed to calculate aggregate yields has been collected only recently. This is especially true for acres of water in annual



production, data that were only available for the years 1971, 1977, 1980-1982, and 1988-1999 (National Agricultural Statistics Service, Catfish Production, various years). Analysis of these data suggested that their limited availability and sensitivity to the sampling methods made them inadequate given the goals of this study. Specifically, yields calculated from the data fluctuated wildly from year to year and were approximately half the reported yields from actual operations in the Mississippi Delta production region (Lutz, 1998). This suggests that total production has been under reported or actual producing water acres over reported (or some combination of both). As an alternative to observed yields, this study incorporated simulated yield data generated by the POND 3.5 computer program.² Weather, and temperature in particular, was the stochastic component chosen to drive the simulations.

Weather was selected as the force behind simulated yield variability because channel catfish feeding varies significantly with temperature and may cease completely when water temperature drops below 10°C to 12°C (50° to 54°F). When feeding stops, yields either fall or require more time and feed to produce (Avault 1996). As a result, pond management during cool months is critical to final production. The weather database used in the simulations was for Jackson, Mississippi, over the 30-year period 1960 to 1990 (National Solar Radiation Data Base 1998).³

²POND 3.5 is a decision support computer program developed to provide researchers with a tool for rapidly analyzing aquaculture systems under different management regimes and to assist in the development of optimal management strategies (Biosystems Analysis Group 1997). Once a desired facility simulation has been set up, multiple runs can be conducted to examine the effects of various pond management scenarios on fish yields and facility-level economics. For this study, POND 3.5 was used only to simulate yields. Details on the parameter specifications used in the biological model for simulating southeastern U.S. catfish production using POND 3.5 are available from the authors and Soto (1999).

³Yearly weather data included time (Julian days), minimum and maximum air temperature (°C), incident solar radiation (kJ/m²/day), solar radiation penetrating the water surface (kJ/m²/day), cloud cover (decimal percent), wind speed (m/s), precipitation (mm/day), and relative humidity (%). All weather data were actual numbers except for solar radiation penetrating the water surface, which was calculated from incident solar radiation data assuming reflective losses of 6 percent. Further, cloud cover data were assumed to be 0.5 for clear conditions.



Under the assumption that different technologies and management schemes affect fish yield, yield distributions were simulated for three different farm sizes and two different culture systems. Farms were categorized by size into small (160 acres), medium (320 acres), and large (640 acres) (Keenum & Waldrop 1988). Channel catfish are usually cultured as food fish by one of two methods — the multiple-batch system, where multiple-size cohorts of fish are cultured within the same pond, and the single-batch system. Multiple-batch production allows a producer to distribute the harvest dates (and cash-flow) throughout the year, but it produces disparity in fish size because of competition between large and small fish for food, which contributes to higher feed conversion ratios (Collier & Schewedler 1990). In the single-batch system, fish are maintained in a single-size cohort to reduce size variability, competition, and feed conversion ratios. The single-batch system may allow producers to better manage inventory and stock growth. However, single-batch systems can lead to problems with product supply to markets and producer cash flow (Avault 1996).

While the simulation of single-batch systems was straightforward, with production defined as beginning on April 1 and ending on November 1 of each year, multiple-batch simulations were complicated by the need to schedule harvesting and restocking at appropriate times of the year. In addition, multiple-batch production is by nature a multiple-year process that can be difficult to compare against the single-year, single-batch system. In this study, multiple-batch simulations consisted of seven different lots over a 3-year period, with each lot having a different start date (April 1, June 1, and August 1 in the first 2 years, and April 1 in the final year). Harvest also occurred on a calendar schedule, with each April stocking being harvested November 1 of the same year. June and August stockings were harvested in June and August of the following year, respectively. These harvest dates were chosen so as to allow the fish to reach a marketable size given the biological growth model. Simulations generated information on total production, average annual yields over the 3-year period, and the amount of feed required for each simulated yield. Simulated results were then validated by research and extension experts familiar with Delta catfish production (Avault 1998; Avery 1998; Lutz 1998).



Price Data

Nominal prices paid to U.S. catfish producers for 1970-1999 were obtained from the National Agricultural Statistics Service (Catfish Production, various years). Annual nominal catfish feed prices were obtained for 1977-1998 from the Mississippi Cooperative Extension Service (Fact Sheet 1998). To the author's knowledge, this feed price data series is the only one to have been collected in the United States over an extended period and, as such, represents a more accurate measure of feed price fluctuations than prices that might be constructed from data for feed components. All nominal data were then converted to real data using price index deflators obtained from the Bureau of Labor Statistics (BLS) (U.S. Department of Commerce 2000). The BLS producer price index of prepared animal feeds (series WPU029) was used to deflate catfish feed prices, and the BLS producer price index of unprocessed finfish was used to deflate prices paid to catfish producers. Because deflated nominal data do not account for the direct impacts of technological change and changes in market structure, further isolation of the random component in the price series was accomplished by detrending, or regressing real prices against time using least squares methods. Residuals were then examined for normality. Failing normality, attempts were made to find the best distribution to represent the stochastic component of price changes.

Estimating Distributions

A variety of approaches were available to determine the appropriate distributions for yields and the stochastic component of prices. Under a parametric approach, a specific distribution could be selected *a priori* and parameters of the distribution estimated using observed data. Non-aquaculture studies have typically used the normal distribution (Krause & Koo 1996; Streeter & Tomek 1992; Coyle 1992; Tronstad & McNeill 1989). Other distributions also have been used, including gamma for soybean yields (Gallagher 1987), beta for corn yields (Nelson & Preckel 1989), an inverse hyperbolic sine transformation for corn yields (Moss & Shonkwiler 1993), and a lognormal distribution for prices of irrigated alfalfa and dryland wheat (Buccola 1986). These alternative distributions allowed for more realistic repre-



sentation of the data in those specific studies. However, the studies still relied on *a priori* specification of a distribution that, if incorrect, could lead to inaccurate predictions and misleading inferences.

Nonparametric approaches were developed to overcome some of the problems associated with the parametric techniques. The simplest approach to nonparametric estimation of a probability density function is the histogram. Alternative approaches for nonparametric analysis include kernel function smoothing, nearest neighbor smoothing, and orthogonal series estimators. Computer software is widely used to non-parametrically fit distributions to data that are used to represent outcomes in studies of actuarial or claims adjustments, science and engineering problems such as oil well drilling, and time between events. BestFit (Palisade Corporation 1997), one of the newest packages for fitting distributions, was employed in this study. When sample data are used to estimate the properties of a specific population, the program sorts the data, gathers statistics, and converts the data to a discrete probability density distribution. The program then sequentially optimizes the goodness-of-fit between the discrete data and a set of theoretical distribution functions. For each distribution examined, the program approximates initial parameters using maximum-likelihood estimators (MLEs). The goodness-of-fit is then optimized using the Marquardt-Levenberg method.⁴ Finally, all estimated functions

⁴ The Marquardt-Levenberg method is a non-linear, least-squares, iterative technique that minimizes a goodness-of-fit statistic. For input distributions that are very smooth, MLEs alone will usually produce reasonable distribution fits. However, if the input distribution is incomplete or not smooth, the Marquardt-Levenberg approach is generally preferred. Goodness-of-fit is defined as the probability of generating the observed data given the estimated parameters, and the statistics are usually used in a relative sense by comparing the values among potential distribution functions. Some of the common tests used for goodness-of-fit are the chi-square test, Kolmogorov-Smirnov test, and Anderson-Darling test. A weakness of the chi-square test is that there are no clear guidelines for selecting histogram intervals, and, in some situations, different conclusions can be reached from the same data, depending on how the intervals are specified. The Kolmogorov-Smirnov test does not depend on the number of intervals, which makes it more robust than the chi-square test. However, the test cannot be used to identify anything but major tail discrepancies among distributions. The Anderson-Darling test is very similar to the Kolmogorov-Smirnov test, but it places more emphasis on tail values and it is more powerful than the Kolmogorov-Smirnov test against many alternative distributions.



are compared, and the ones with the best goodness-of-fit statistics are considered the appropriate distributions to represent the data. Yield distributions were directly estimated from simulated yield data. In the case of prices, distributions were estimated for the stochastic component after the effects of inflation and structural change were removed from the data.

Generating Net Return Distributions

A three-step process was used to generate net return distributions for each combination of farm size and batch system. First, a Mississippi Delta-based budget for catfish enterprises was developed as a spreadsheet template. The form of this budget model is presented in Table 1. Engle & Kouka (1996) had updated this general budget from Keenum & Waldrop (1988) assuming yields of 5,000 lb/acre/year, an 11 percent interest on operating costs for 9 months, and water acres of 140, 284, and 569 for 160-, 320-, and 640-acre farms, respectively. The costs used in their budget model implicitly reflected efficiency levels associated with the top 10 percent of catfish producers in the southeastern United States.

Once the basic model was identified, the second step required defining sources of stochasticity in the deterministic budget. As previously discussed, the stochastic variables were defined as the producer price for catfish, catfish yields, and the producer price of catfish feed. These stochastic variables were inserted into the budget model as the estimated probability distributions. One consequence of specifying stochastic yields was the necessity of calculating the amount of feed fed for every generated yield in order to obtain total feed cost. To obtain a relationship between yield and the amount of feed fed, feed fed was regressed against yields using data generated by the POND 3.5 simulations.

The third step required using the now stochastic budget model to generate net return distributions. This simulation process involved repeated calculation of the budget, each time sampling from the stochastic variable distributions. This Monte Carlo approach to simulation can require a large number of samples to approximate an input distribution, especially if the input distributions are highly skewed or have outcomes of low probability. However, with enough iterations, the sample values become distributed in a manner that approximates the input probability



Table 1. An example of the budget framework for catfish production in the Mississippi Delta (shaded entries denote stochastic variables that were replaced by probability distributions in net return simulations)

ITEM	Farm Size		
	160 acre	320 acre	640 acre
INCOME			
Catfish yield	700,000	1,420,000	2,845,000
Catfish price (\$/lb.)	0.77	0.77	0.77
TOTAL INCOME	540,750	1,096,950	2,197,763
TOTAL INCOME PER ACRE	3,863	3,863	3,863
OPERATING COSTS			
FIXED OPERATING COSTS			
REPAIRS AND MAINTENANCE	12,000	20,000	36,000
POND RENOVATION	7,200	13,000	23,000
ALL FUEL (electricity, diesel, gas & oil)	18,698	37,995	76,000
CHEMICALS	485	985	2,000
TELEPHONE	2,000	2,500	3,100
WATER QUALITY	0	450	2,000
FINGERLINGS	42,000	85,200	136,560
LABOR	36,660	85,000	182,963
MANAGEMENT	21,000	35,000	60,000
HARVESTING & HAULING	28,000	56,800	85,350
ACCOUNTING/LEGAL	1,800	2,400	3,500
BIRD SCARING AMMUNITION	1,000	2,000	4,000
SUBTOTAL FIXED OPERATING COSTS	170,843	341,330	614,473
INTEREST ON FIXED OPERATING COSTS	14,095	28,160	50,694
TOTAL FIXED OPERATING COSTS	184,938	369,490	665,167



VARIABLE OPERATING COSTS			
FEED (TON)	770	1562	3129
PRICE OF FEED/TON	280	280	280
SUBTOTAL VAR. OPERATING COSTS	215,600	437,360	876,120
INTEREST ON FEED	17,787	36,082	72,280
TOTAL VARIABLE OPERATING COSTS	233,387	473,442	948,400
TOTAL OPERATING COSTS	418,325	842,932	1,613,567
OPERATING COSTS PER ACRE	2,988	2,968	2,836
FIXED OWNERSHIP COSTS			
DEPRECIATION			
Ponds	13,608	26,046	52,155
Water supply	5,000	10,000	20,000
Office building	900	1,450	2,250
Feed storage	520	1,040	1,300
Equipment	32,533	60,517	119,012
INTEREST ON INVESTMENT			
Land	17,930	35,530	70,730
Pond construction	7,485	14,325	28,685
Water supply	2,750	5,500	11,000
Equipment	12,575	22,743	44,084
TAXES AND INSURANCE	2,000	4,000	6,000
TOTAL OWNERSHIP COSTS	95,301	181,151	355,216
OWNERSHIP COSTS PER ACRE	681	638	624
TOTAL COSTS PER ACRE	3,669	3,606	3,460
RESIDUAL RETURNS PER ACRE	194	257	402



distributions. More important, as more iterations are executed, the output (in this case, net returns) distributions become more stable and less sensitive to additional generated information. A convergence criterion of 0.5 percent was used to terminate all simulations. In addition, a constant, non-zero seed value was used for the random number generator across all simulations. The random number generator was used to guide sampling from the stochastic variable distributions, and the use of a constant seed value resulted in the exact same sequence of random numbers for each simulation, thereby allowing for direct comparisons among the generated net return distributions. Identification of the best distribution to capture the variability associated with the simulated net returns was accomplished using BestFit in the same manner as it was used to identify the stochastic price and yield distributions.

Risk Efficiency Analysis

The final facet of this study involved identifying the best farm size/batch system combination given the presence of stochastic economic variables. The simulated distributions of net returns were used to examine the effects of risk. A generalized stochastic dominance program (GSDP) developed by Goh et al. (1989) was used to compare the net return distributions obtained for the 6 scenarios, with second-degree stochastic dominance efficiency being the criteria. One limitation of the GSDP was that it could compare empirical distributions of no more than 200 observations. To obtain net return distributions of that specific size, a Latin Hypercube method was used to sample from the estimated net return probability distributions generated via the Monte Carlo simulations.

Latin Hypercube sampling (LHS) was first proposed by McKay et al. (1979) as an alternative to simple random sampling in computer experiments. The method is similar to stratified sampling, but it ensures that each of the input variables has all portions of its distribution represented in the final sample. The procedure accomplishes this by dividing the range of each variable into strata of equal marginal probability and sampling once from each stratum. More precisely, stratification divides the cumulative density function into equal probability intervals and



randomly samples without replacement from within each interval. LHS is preferred to the standard Monte Carlo simulation approach in situations where low probability outcomes are represented in input probability distributions or where the number of allowable iterations is constrained.



Results and Discussion

The first three parts of this section examine the estimated distributions of yields, catfish prices, and feed prices. The fourth section focuses on a discussion of the stochastic budget simulations and the resulting net returns distributions. Last, results of the risk efficiency analysis are described.

Yield Distributions

Tables 2 and 3 show the statistical results obtained when fitting theoretical probability distributions to simulated single- and multiple-batch yield data using BestFit. Only the top 3 statistically ranked distributions are shown (out of the 38 potential distributions analyzed). Given the need to choose just one distri-



Table 2. Statistical results from fitting theoretical distributions to simulated single-batch production yields using BestFit

	Single Batch Simulated Data	Estimated Weibull Distribution	Estimated Normal Distribution	Estimated Gamma Distribution
Minimum Value	5039.11			
Maximum Value	6252.08			
Mean	5657.13	5650.38	5657.13	5657.13
Median	5681.07	5696.57	5657.13	5651.73
Standard Deviation	305.67	330.56	305.67	302.82
Skewness	-0.41	-0.80	0.00	0.11
Kurtosis	2.42	3.76	3.00	3.02
Chi-square Test				
Test Statistic		7.74	7.91	8.23
Reject/Fail to Reject H_0^*		Fail to Reject	Fail to Reject	Fail to Reject
Rank Among Distributions		1	2	3
Kolmogorov-Smirnov Test				
Test Statistic		0.10	0.11	0.11
Reject/Fail to Reject H_0^*		Fail to Reject	Fail to Reject	Fail to Reject
Rank Among Distributions		2	3	5
Anderson-Darling Test				
Test Statistic		0.27	0.33	0.38
Reject/Fail to Reject H_0^*		Fail to Reject	Fail to Reject	Fail to Reject
Rank Among Distributions		1	2	4

* H_0 : Simulated data generated by given theoretical probability distribution. Critical value chosen at $\alpha=0.05$.

tribution for use in the stochastic budget model, the results unambiguously suggest that the most appropriate distribution for single-batch yield was the Weibull distribution because it was ranked higher than all other alternatives by each goodness-of-fit statistic (Table 2). For the single-batch yields, the chi-square test fails to reject the null hypothesis of Weibull distribution at the 0.05 level of significance ($\chi^2=7.737$). The Kolmogorov-Smirnov and Anderson-Darling tests also supported the Weibull distribution at the 5 percent level of significance. A histogram depiction of the



Table 3. Statistical results from fitting theoretical distributions to simulated multiple-batch production yields using BestFit

	Multiple Batch Simulated Data	Estimated Normal Distribution	Estimated Erlang Distribution	Estimated Gamma Distribution
Minimum Value	5065.79			
Maximum Value	6085.96			
Mean	5605.97	5605.97	5605.97	5605.97
Median	5616.67	5605.97	5602.30	5602.30
Standard Deviation	251.99	251.99	248.48	248.46
Skewness	-0.22	0.00	0.09	0.09
Kurtosis	2.44	3.00	3.01	3.01
Chi-square Test				
Test Statistic		2.09	2.30	2.30
Reject/Fail to Reject H_0^*		Fail to Reject	Fail to Reject	Fail to Reject
Rank Among Distributions		1	2	3
Kolmogorov-Smirnov Test				
Test Statistic		0.12	0.12	0.12
Reject/Fail to Reject H_0^*		Fail to Reject	Fail to Reject	Fail to Reject
Rank Among Distributions		4	6	5
Anderson-Darling Test				
Test Statistic		0.26	0.28	0.28
Reject/Fail to Reject H_0^*		Fail to Reject	Fail to Reject	Fail to Reject
Rank Among Distributions		1	2	3

* H_0 : Simulated data generated by given theoretical probability distribution. Critical value chosen at $\alpha = 0.05$.

simulated data and the fitted distribution is given in Figure 3. For simulated multiple-batch yields, goodness-of-fit statistics suggest the use of a normal distribution, although the Kolmogorov-Smirnov test indicated that there may be other preferred distributions in the absence of the other statistical tests (Table 3, Figure 4). For multiple-batch production, the chi-square test fails to reject the null hypothesis of normality at the 5 percent level of significance. The Kolmogorov-Smirnov and Anderson-Darling tests also supported normality at the 5 percent level of significance.



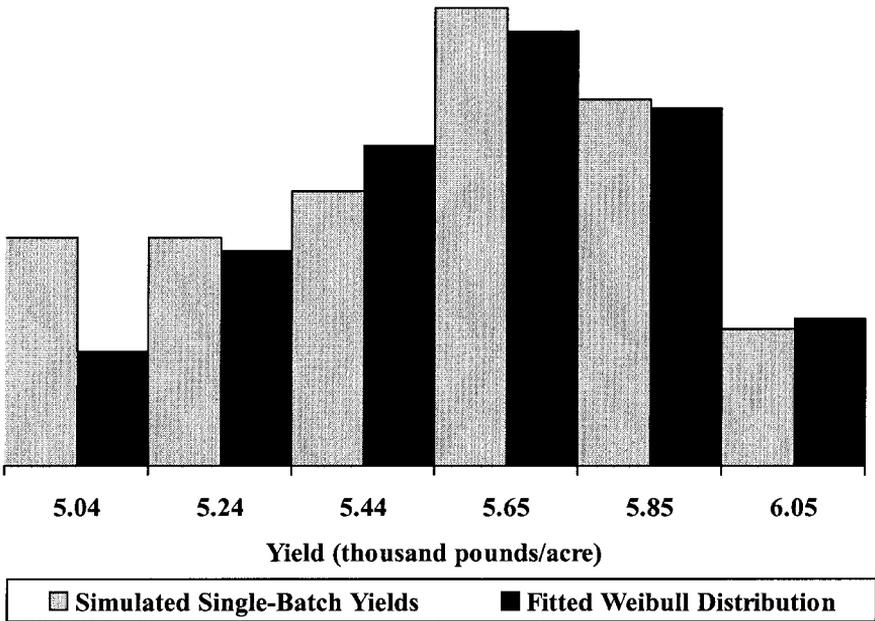


Figure 3. Comparison of simulated single-batch catfish yields and Weibull distribution estimated using BestFit.

Given the calculated single-batch mean and median yields of 5657 and 5681 pounds per acre, producers may experience higher than average yields. If producers assume single-batch yield normality, then two possible decision-making errors might occur: underestimation of the most likely yields and underestimation of chances of extremely low yields. The latter potential error arises because of the fitted Weibull distribution’s negative skewness, and it reinforces the yield nonnormality that is widely observed in row-crop agriculture. For example, Ramirez (1997) found that corn and soybeans yield distributions were significantly skewed to the left and related the results to weather and pests incidents. Gallagher (1987) also determined that national average soybean yields were negatively skewed with a relatively high chance of low yields. He concluded that skewed yields were a consequence of weather conditions. Goodwin & Ker (1998) used Kernel smoothing techniques to evaluate county-level crop yield distributions and found significant negative skewness for corn and

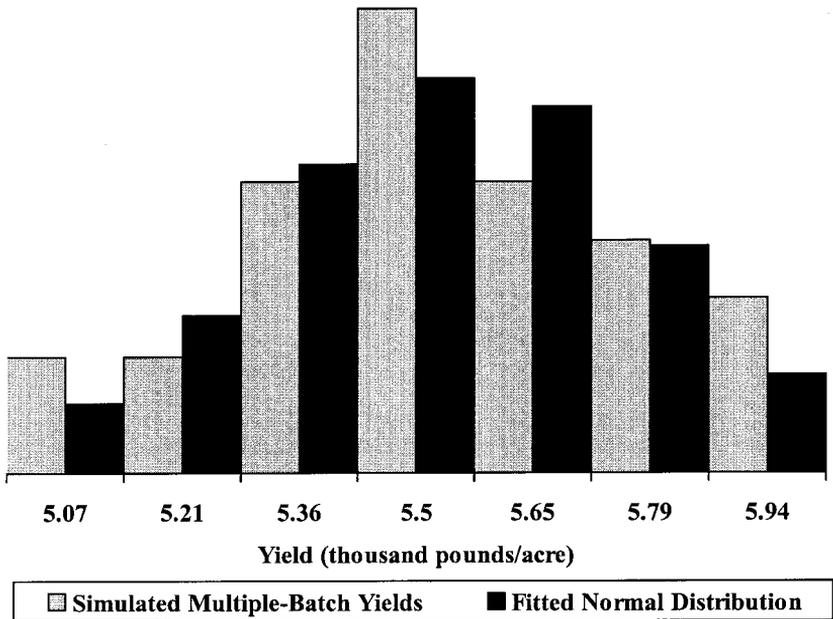


Figure 4. Comparison of simulated multiple-batch catfish yields and normal distribution estimated using BestFit.

wheat and very slight positive skewness for cotton, grain sorghum, and barley. Tirupattur et al. (1996) also found that corn and yield distributions were negatively skewed and best described by a beta distribution.

Normality in the simulated multiple-batch yields was not expected, especially given the non-normal results associated with simulated single-batch yields. However, given that an average annual yield for a 3-year production cycle was used in the analysis, the results may indicate another potential benefit to multiple-batch production. Specifically, multiple-batch methods may allow producers to smooth the effects of year-to-year variations in weather, thereby moderating the impact of weather on their decision-making process. If multiple-batch production can be demonstrated to generate normally distributed yields in the field, then this production method might be preferred, based on the ability of producers to consistently estimate future production without underestimating the chances of very low yields.



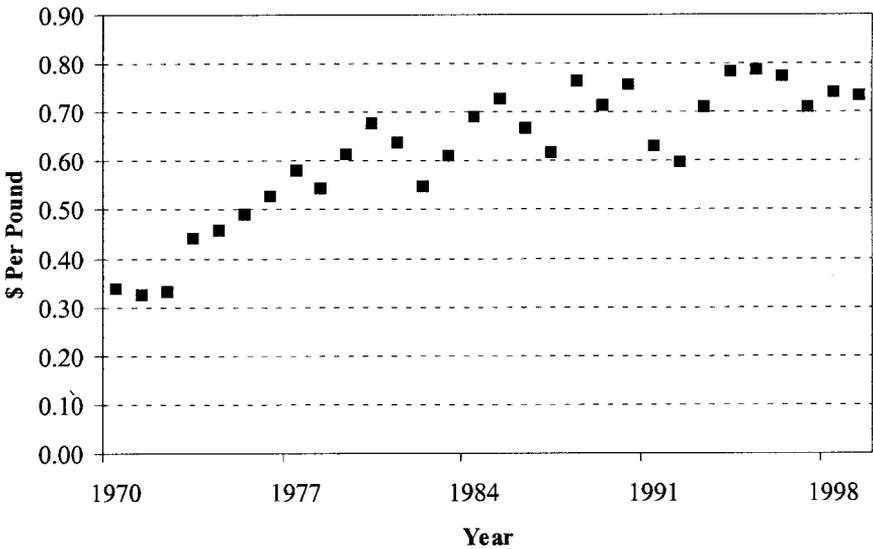


Figure 5. Nominal prices paid to U.S. catfish producers, 1970-1999. Source: National Agricultural Statistics Service (NASS), Agricultural Statistics Board, U.S. Department of Agriculture.

Catfish Price Distribution

Nominal prices paid to catfish producers (Figure 5) were deflated using the price index of unprocessed finfish. After deflating, visual inspection of the real prices indicated a downward trend, perhaps because of the impact of technological change and/or changes in market structure (Figure 6). Further isolation of the random component in the catfish price series was accomplished by regressing the natural logarithm of real price against time (Table 4). Tests indicated that the residuals were neither autocorrelated (independence of errors in two separated time periods) nor heteroskedastic (residuals and prices are not related). The estimated Durbin-Watson (DW) statistic for the residuals was 1.53, which was larger than $d_u = 1.47$, the critical 5 percent upper value of DW. Heteroskedasticity tests values were lower than the 3.84 critical chi-square value.⁵

⁵ Although the autocorrelation and heteroskedasticity tests are based on the assumption of normality in the residuals, the least squares estimator will still be unbiased, minimum variance, and consistent from within the class of linear unbiased estimators, even in the presence of nonnormal error distributions (Judge et al. 1985).



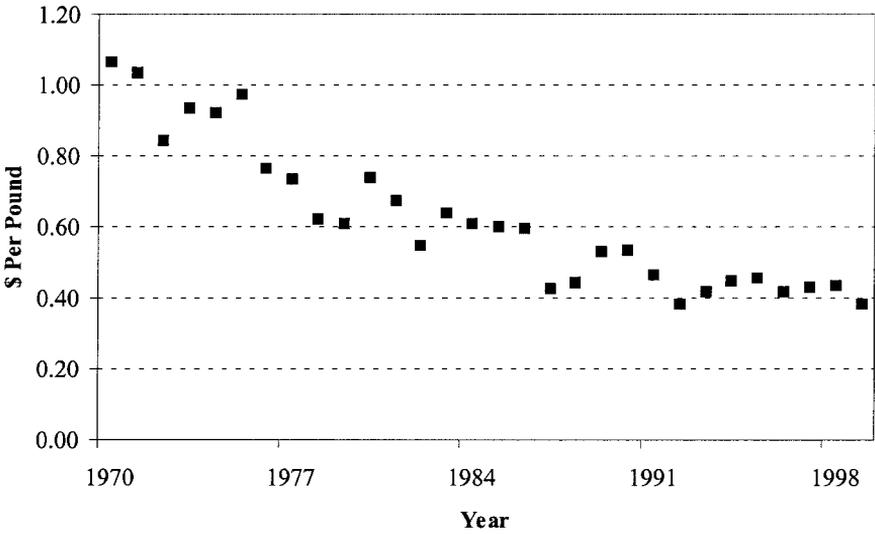


Figure 6. Real prices paid to U.S. catfish producers, 1970-1999.
Source: National Agricultural Statistics Service (NASS),
Agricultural Statistics Board, U.S. Department of Agriculture.

Table 4. Parameter estimates and statistics for price detrending and feed fed regressions used in developing the stochastic budget model (t-statistic for the estimate in parentheses)

	Dependent Regression Variable			
	Natural Log of Real Catfish Price (\$)	Natural Log of Real Feed Price (\$)	Single Batch Feed Fed (tons)	Multiple Batch Feed Fed (tons)
Intercept	0.023	5.640	-2.2374 (-8.6611)	-0.7104 (-3.7576)
Time	-0.036 (-13.530)	-0.022 (-8.107)		
Yield			0.0014 (30.5141)	0.0011 (32.5908)
R ²	0.88	0.78	0.97	0.97
F Statistic	4.29	4.38	4.18	4.23
Durbin-Watson	1.53	1.64	n.a.	n.a.



Table 5. Statistical results from fitting theoretical distributions to catfish price residuals using BestFit

	Catfish Price Residuals	Estimated Triangular Distribution	Estimated Error Function Distribution	Estimated Normal Distribution
Minimum Value	-0.226	-0.240		
Maximum Value	0.167	0.176		
Mean	0.000	0.011	0.000	0.026
Median	0.037	0.025	0.000	0.026
Standard Deviation	0.106	0.060	0.110	0.118
Skewness	-0.872	-0.486	0.000	0.000
Kurtosis	2.084	2.387	3.000	3.000
Chi-square Test				
Test Statistic		7.268	13.500	13.112
Reject/Fail to Reject H_0^*		Fail to Reject	Reject	Reject
Rank Among Distributions		1	3	2
Kolmogorov-Smirnov Test				
Test Statistic		0.160	0.157	0.202
Reject/Fail to Reject H_0^*		Fail to Reject	Fail to Reject	Reject
Rank Among Distributions		2	1	6
Anderson-Darling Test				
Test Statistic		0.966	1.042	1.357
Reject/Fail to Reject H_0^*		Fail to Reject	Fail to Reject	Reject
Rank Among Distributions		1	2	3

* H_0 : Simulated data generated by given theoretical probability distribution. Critical value chosen at $\alpha=0.05$.

BestFit was used to determine the probability distribution of the random component of real catfish prices paid to producers. Table 5 shows the statistical results obtained for the analysis, and they suggest that the random component can be best approximated using a triangular distribution with negative skewness (Figure 7). The chi-square test failed to reject the null hypothesis of triangular distribution at the 5 percent level of significance. The Kolmogorov-Smirnov and Anderson-Darling tests also supported the triangular distribution at the 5 percent level of significance. Consequently, assuming normality for real catfish price residuals



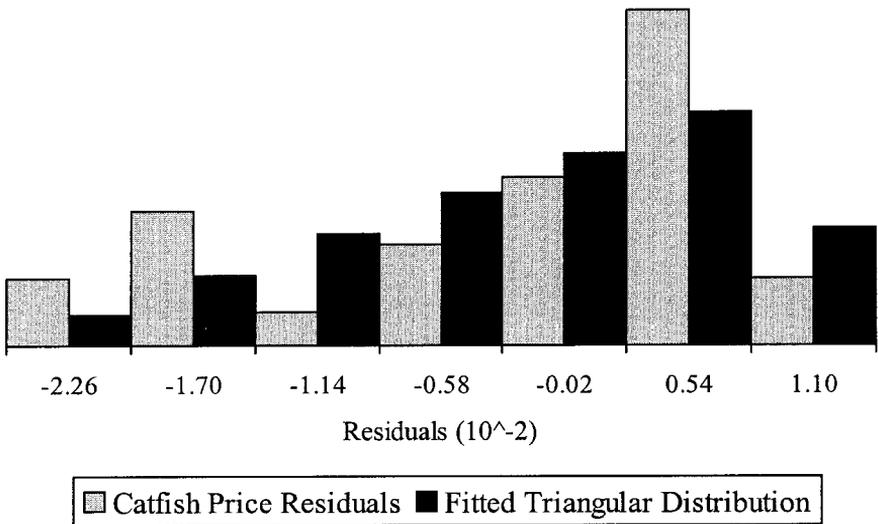


Figure 7. Comparison of the natural log of real catfish price residuals and the triangular distribution estimated using BestFit.

could lead to underestimation of the most likely price and underestimation of the chances of extremely low prices.

Previous research has reported varying results with respect to product prices. Venkateswaran et al. (1993) found that 19 of 31 commodity price data sets had statistically significant skewness, with positive skewness being more prevalent than negative skewness. Mizon et al. (1990) found negative skewness in the standardized log of consumer prices for 30 of 46 months. In contrast, O'Brien et al. (1996) found that forecasted corn futures price distributions were positively skewed throughout the 1992 to 1994 growing season.

Feed Price Distribution

A procedure similar to the one described for catfish prices was conducted to determine the distribution of the random component causing variability in feed prices. Nominal feed prices (Figure 8) were deflated using the price index of prepared animal feeds, after which visual inspection of the real prices indicated a downward trend (Figure 9). Real feed price data were then



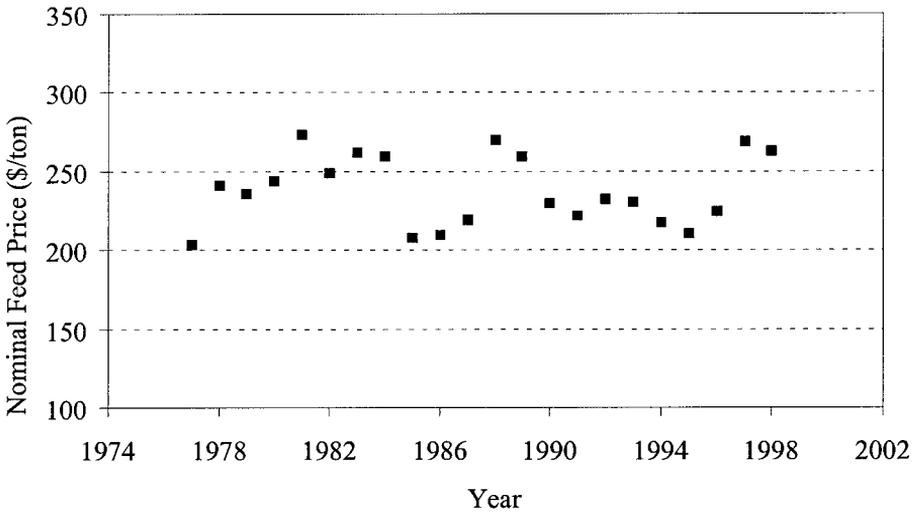


Figure 8. Nominal prices for catfish feed (\$/ton), 1977-1997. Source: Mississippi Cooperative Extension Service Fact Sheet, 1998.

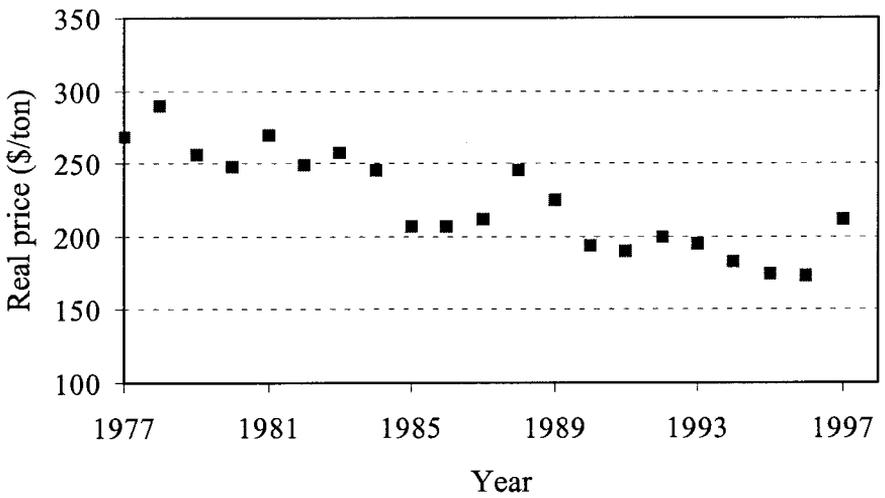


Figure 9. Real prices for catfish feed (\$/ton), 1977-1997. Source: Mississippi Cooperative Extension Service Fact Sheet, 1998.

detrended by regressing the natural logarithm of real feed prices against time (Table 4). Results from the linear regression estimation demonstrated that the model was significant and the trend in prices consistent over time. Tests of heteroskedasticity and autocorrelation indicated that the residuals were neither autocorrelated nor heteroskedastic. The estimated DW statistic for residuals equaled 1.64, which was larger than $d_u = 1.42$, the critical 5 percent upper value of DW. Estimated heteroskedasticity test values were lower than the 3.84 critical chi-square at a 5 percent level of significance.

Table 6 presents the statistical results obtained when fitting distributions to the residuals of catfish feed prices. The chi-square, Kolmogorov-Smirnov, and Anderson-Darling tests support the extreme value distribution with positive skewness as being the best distribution to represent the data. Figure 10 shows the com-

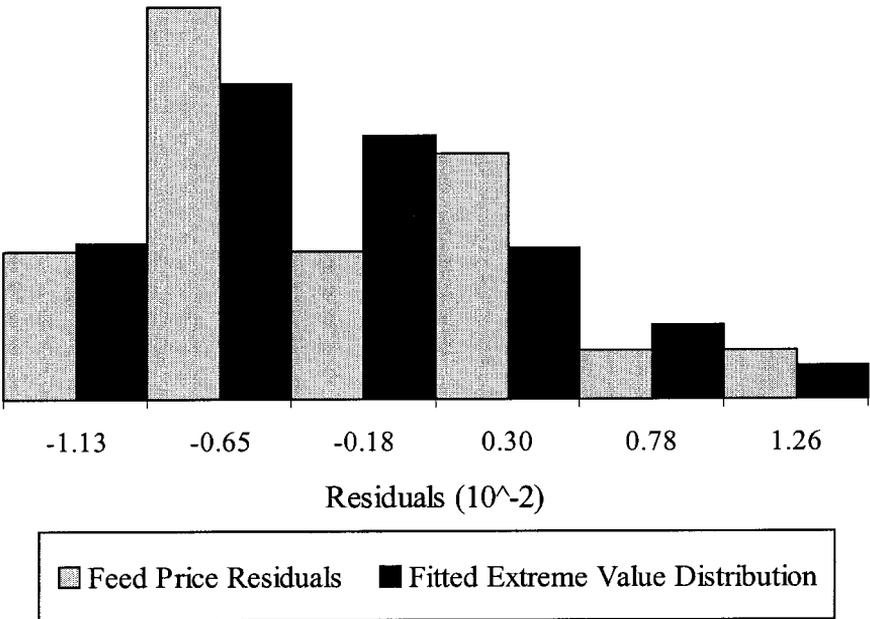


Figure 10. Comparison of the natural log of real feed price residuals and the extreme value distribution estimated using BestFit.

Table 6. Statistical results from fitting theoretical distributions to catfish feed price residuals using BestFit

	Catfish Feed Price Residuals	Estimated Extreme Value Distribution	Estimated Gamma Distribution	Estimated Weibull Distribution
Minimum Value	-0.113		-0.116	-0.116
Maximum Value	0.173			
Mean	0.000	0.000	0.005	0.002
Median	-0.024	-0.012	-0.011	-0.009
Standard Deviation	0.073	0.073	0.075	0.069
Skewness	0.929	1.140	1.244	0.754
Chi-square Test				
Test Statistic		2.953	2.796	2.945
Reject/Fail to Reject H_0^*		Fail to Reject	Fail to Reject	Reject
Rank Among Distributions		4	2	3
Kolmogorov-Smirnov Test				
Test Statistic		0.101	0.106	0.114
Reject/Fail to Reject H_0^*		Fail to Reject	Fail to Reject	Reject
Rank Among Distributions		3	4	6
Anderson-Darling Test				
Test Statistic		0.223	0.379	0.314
Reject/Fail to Reject H_0^*		Fail to Reject	Fail to Reject	Reject
Rank Among Distributions		1	2	5

* H_0 : Simulated data generated by given theoretical probability distribution. Critical value chosen at $\alpha=0.05$.

parison of residuals from the regression against the estimated extreme value distribution. Given these results, an assumption of normality for the distribution of feed price residuals could lead to overestimation of the most likely price and underestimation of the chances of extremely high prices.



Net Return Distributions

Six budgets for catfish enterprises, including three farm sizes and two production systems, were used to simulate net return distributions. Catfish yields, price of catfish paid to producers, and feed prices were the stochastic variables. Weibull and normal distributions for single and multiple-batch yields, respectively, were entered in the budget model as input variables. During simulation, sampling from these distributions was conducted to generate the net returns.

Catfish yields were sampled directly from the estimated distributions. Associated with each yield was the amount of feed needed to generate the yield. These feed-to-yield relationships, which imply feed conversion ratios between 1.4 (for single batch) and 2.2 (for multiple-batch), were statistically estimated from the yield simulation data (Table 4) and incorporated into the budget model.

Price paid to producers was determined the same way for all six budget scenarios. First, the expected real price was forecasted using the deterministic trend information. Next, a sample from the triangular probability distribution estimated for the random component of price was added to the expected real price, with the resulting real price inflated to obtain the nominal price. A similar procedure was used to obtain the catfish feed price used for each budget simulation. Distributions of net returns were then generated using Monte Carlo techniques, with each simulation converging in approximately 500 iterations.

After simulation, BestFit was used to determine the probability distributions of the simulated net returns. Table 7 shows the statistical results obtained from analysis of net returns for the three farm sizes using a single-batch production system. Net returns for single-batch production were best described with a negatively skewed beta distribution for all farm sizes, suggesting that higher than average returns are likely to occur for single-batch systems in the Mississippi Delta (figures 11, 12, 13). Consequently, assuming normality for single-batch net returns could lead to underestimation of the most likely net returns and underestimation of extremely low net returns. Similar results were found for multiple-batch production systems (Table 8; figures 14, 15, 16).



Table 7. Statistical results from fitting theoretical distributions to simulated net returns for single-batch production using BestFit

	Farm Size in the Budget Simulation					
	160 acres		320 acres		640 acres	
	Simulated Data	Beta Distrib.	Simulated Data	Beta Distrib.	Simulated Data	Beta Distrib.
Minimum Value	-292.40	-293.23	-218.45	-219.29	-67.44	-68.30
Maximum Value	4356.32	4357.15	4433.75	4434.58	4586.44	4587.30
Mean	2257.91	2257.91	2333.87	2333.87	2485.84	2485.84
Median	2288.31	2298.64	2364.19	2374.59	2516.12	2526.57
Standard Deviation	1032.14	1032.14	1032.46	1032.46	1032.62	1032.62
Skewness	-0.29	-0.14	-0.29	-0.14	-0.29	-0.14
Kurtosis	2.21	1.84	2.21	1.85	2.21	1.85
Chi-square Test						
Test Statistic		28.29		27.55		27.52
Reject/Fail to Reject H_0^*		Fail to Reject		Fail to Reject		Fail to Reject
Rank Among Distributions		1		1		1
Kolmogorov-Smirnov Test						
Test Statistic		0.03		0.03		0.03
Reject/Fail to Reject H_0^*		Fail to Reject		Fail to Reject		Fail to Reject
Rank Among Distributions		1		1		1
Anderson-Darling Test						
Test Statistic		0.49		0.49		0.49
Reject/Fail to Reject H_0^*		Fail to Reject		Fail to Reject		Fail to Reject
Rank Among Distributions		1		1		1

* H_0 : Simulated data generated by given theoretical probability distribution. Critical value chosen at $\alpha=0.05$.



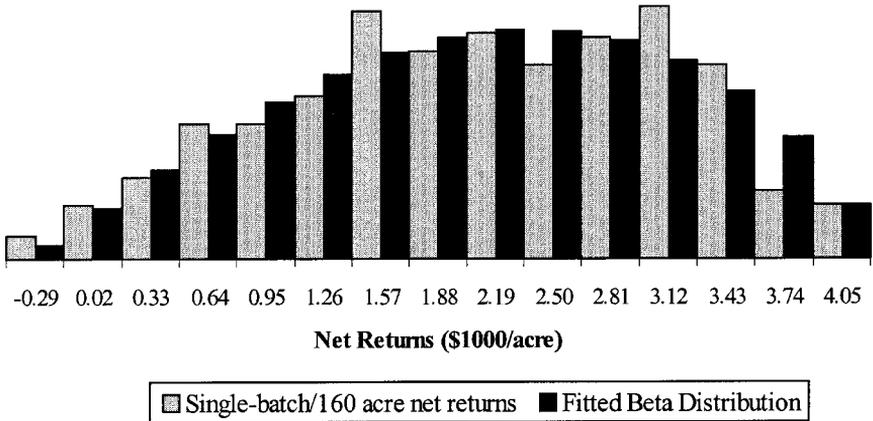


Figure 11. Comparison of actual versus fitted net return distributions for the single-batch/160 acre simulation scenario.

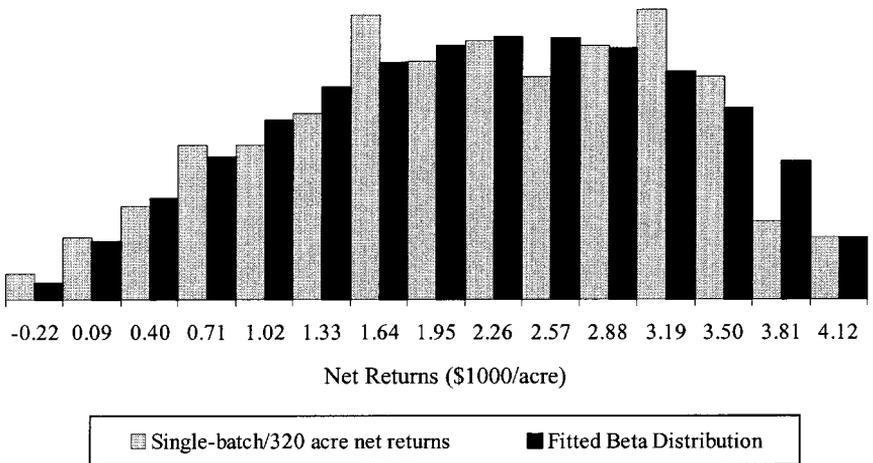


Figure 12. Comparison of actual versus fitted net return distributions for the single-batch/320 acre simulation scenario.



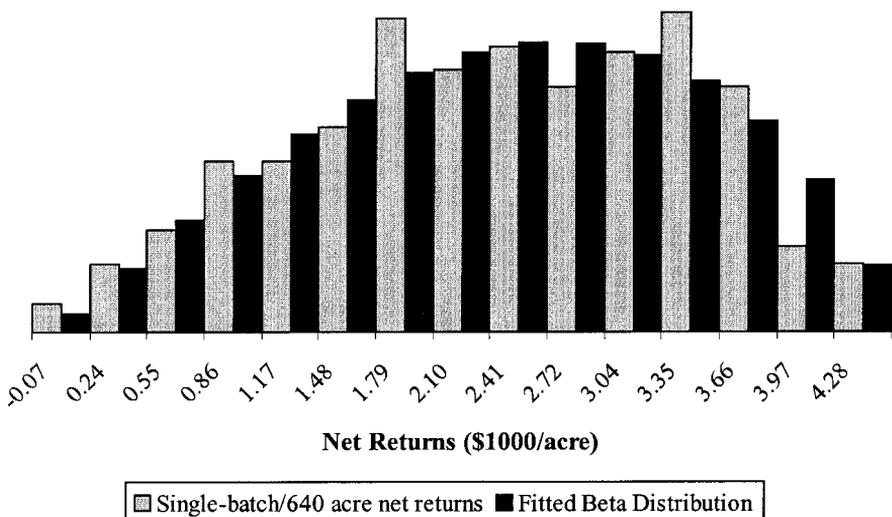


Figure 13. Comparison of actual versus fitted net return distributions for the single-batch/640 acre simulation scenario.

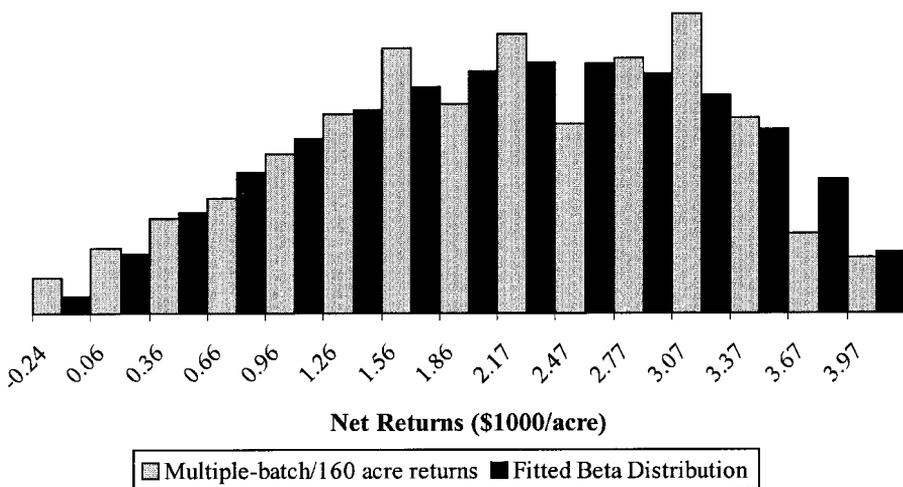


Figure 14. Comparison of actual versus fitted net return distributions for the multiple-batch/160 acre simulation scenario.

Table 8. Statistical results from fitting theoretical distributions to simulated net returns for multiple-batch production using BestFit

	Farm Size in the Budget Simulation					
	160 acres		320 acres		640 acres	
	Simulated Data	Beta Distrib.	Simulated Data	Beta Distrib.	Simulated Data	Beta Distrib.
Minimum Value	-238.38	-238.55	-163.90	-164.07	-12.64	-12.81
Maximum Value	4268.58	4268.75	4345.17	4345.35	4497.46	4497.64
Mean	2226.31	2226.31	2301.85	2301.85	2453.63	2453.63
Median	2245.26	2265.20	2320.92	2340.72	2472.75	2492.48
Standard Deviation	1008.78	1008.78	1008.94	1008.94	1009.02	1009.02
Skewness	-0.34	-0.14	-0.34	-0.14	-0.34	-0.14
Kurtosis	2.22	1.84	2.22	1.84	2.22	1.84
Chi-square Test						
Test Statistic		26.86		26.89		26.90
Reject/Fail to Reject H_0^*		Fail to Reject		Fail to Reject		Fail to Reject
Rank Among Distributions		1		1		1
Kolmogorov-Smirnov Test						
Test Statistic		0.04		0.04		0.04
Reject/Fail to Reject H_0^*		Fail to Reject		Fail to Reject		Fail to Reject
Rank Among Distributions		1		1		1
Anderson-Darling Test						
Test Statistic		0.73		0.72		0.72
Reject/Fail to Reject H_0^*		Fail to Reject		Fail to Reject		Fail to Reject
Rank Among Distributions		1		1		1

* H_0 : Simulated data generated by given theoretical probability distribution. Critical value chosen at $\alpha=0.05$.



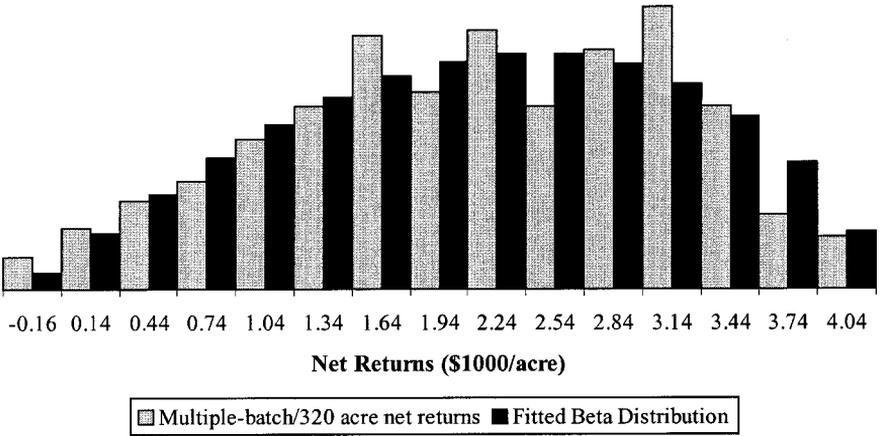


Figure 15. Comparison of actual versus fitted net return distributions for the multiple-batch/320 acre simulation scenario.

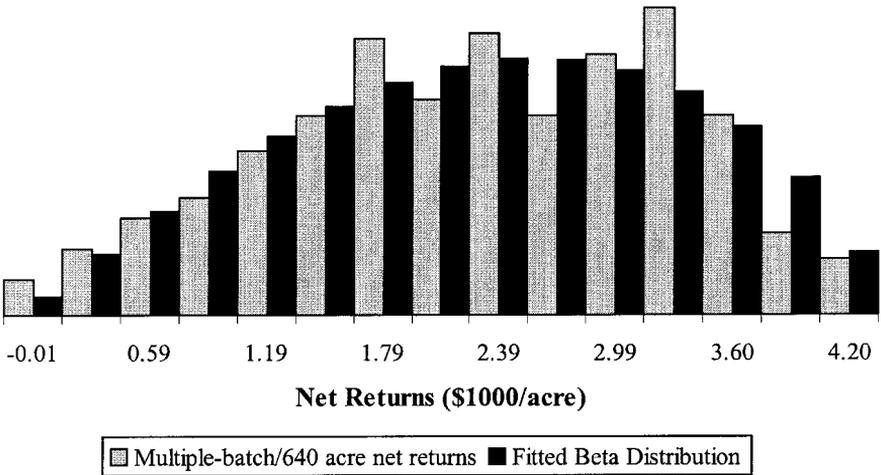


Figure 16. Comparison of actual versus fitted net return distributions for the multiple-batch/640 acre simulation scenario.

Risk Efficiency Analysis

Once net return distributions were simulated under the six budget scenarios, a generalized stochastic dominance program developed by Goh et al. (1989) was used to evaluate the risk efficiency of the different farm size/batch system combinations. Results suggest that the largest farms, under both multiple- and single-batch production systems, second-degree stochastically dominated medium and small farms (Figure 9). These results also suggest that economies of scale may be operating in the south-eastern U.S. catfish production industry, or that after adjusting all inputs optimally, the unit cost of production can be reduced by increasing the size of a producer's operation. Of course, the preference of any particular alternative over another depends on the relative risk and return of the alternative and the risk attitudes of the decision maker. The second-degree stochastic dominance presented in Figure 17 assumes that all producers are risk averse.

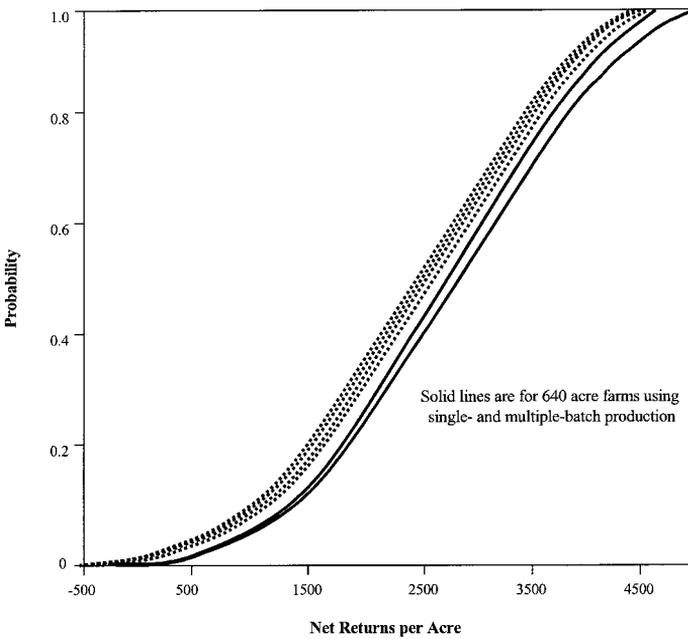


Figure 17. Comparison of the cumulative probability distributions for simulated net returns per acre for all farm size/batch system combinations (solid lines indicate distributions that were second-degree stochastic dominant).



After the efficient set was identified, the inefficient farm size/production system combinations were analyzed separately using second degree stochastic dominance. Results indicated that single- and multiple-batch systems for medium farms were second-degree stochastic dominant with respect to either production system on small farms. This result reinforces the suggestion that economies of scale are at work in the industry, and it implies that small aquaculture operations may not be economically viable, given the risky environment they face.



Conclusions

The main goal of this study was to examine the impact of stochastic price and yield variables on net returns to catfish production. Results indicated that nonnormal distributions of prices and yields generate beta distributed net returns for all combinations of production systems and farm sizes. If these beta distributions describe reality, but the risk averse producer assumes his expected returns are normally distributed, then he or



she will underestimate the probability of obtaining low net returns. Thus, under an assumption of normality, producers may make decisions that place their operations in greater financial peril than they otherwise would if they understood the true distribution of their expected net returns.

Results also showed that the single-batch production system for small farms was the most inefficient technology/size combination. These results were expected since one of the main reasons farmers choose to work with the multiple-batch production technique is to have a steady cash flow through the year and avoid losses caused by unpredictable circumstances. However, a serious problem could arise with multiple-batch systems at certain times of the year — the off-flavor condition. When fish are off-flavor, producers have to wait several weeks until fish return to on-flavor, implying additional costs. Extending the period of production because of off-flavor also can lead to yield losses from diseases and bird predation.

The results obtained in this study also have implications for the possibility of revenue insurance for aquaculture enterprises. This type of insurance has been proposed as a result of the 1996 U.S. FAIR Act, which altered the government's role in providing support to agricultural producers (Skees et al. 1998). As a consequence of this lack of support, there is a renewed interest in agricultural risks and alternative ways to mitigate those risks. Since aquaculture operates without direct government support programs, revenue risk insurance could be an attractive alternative for aquaculturists. Distributions of net returns will be necessary to calculate the risk-adjusted premiums of revenue insurance.

The methods used in this study could easily be extended to comparing other types of technologies in the catfish industry. For example, one possibility would be to study the risk of net returns associated with the cost of fingerlings and fingerling production techniques. To extend the risk analysis, regional budgets need to be improved to better represent catfish enterprises by regions and by type of technology. Information of this type would allow researchers and extension specialists to better educate farmers as to the risk-adjusted advantages and disadvantages of specific technologies.



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