ACREAGE PLANTING DECISION ANALYSIS OF SOUTH CAROLINA TOMATOES: NERLOVIAN VERSUS JUST RISK MODEL

T. T. Fu, S. M. Fletcher, and J. E. Epperson

Abstract

Factors which explain supply response behavior of South Carolina tomato growers were determined. Two well known supply response models were used for comparison: the Nerlovian structural model and the Just risk model. The Just risk model reflected the significance of the risk effect in both stable and unstable periods. An evaluation of forecasting power between the two models was indeterminate. Growers are apparently willing to invest in more information with increased market instability because growers were influenced by the Florida winter price of tomatoes in planting decisions during the period of instability.

Key words: supply response, uncertainty, information, tomatoes.

South Carolina has become an important seasonal source of fresh market tomatoes. The market share of South Carolina tomatoes in the United States market in late spring increased from nearly 7 percent in the 1950's, to around 20 percent currently.[1] Wells has developed a model for forecasting South Carolina tomato prices prior to planting. The forecasting capability of this model was shown to be quite accurate. Thus, the findings of Wells' study provide a partial basis for a study of the supply response behavior of South Carolina tomato producers. The purpose of this paper then is to determine the variables which explain supply response behavior of South Carolina tomato producers. Further, two well known supply response formulations are evaluated to ascertain the importance of risk in terms of explanatory and forecasting power.

Farmers' decisions to plant a certain number of acres are based on the information available before planting. Traditional approaches to analyze decisionmaking by farmers have been concerned with the effect of price expectations formulated from past prices. In recent years, several researchers have incorporated uncertainty in supply response models using different formulations of risk variables. Various formulations of risk have been used to explain the variability of decision variables.

The concept of risk as it affects behavioral decisionmaking originated from the principle of Bernoullian expected utility; i.e., the producer was assumed to maximize expected utility from profit (or other outcomes) rather than expected profit. It has been assumed by empiricists either that the underlying utility function was quadratic or that profit is normally distributed yielding the function of mean and variance only (Young). Thus, variance or standard deviation becomes the appropriate measure of risk. An increase in risk will have a negative effect on expected utility since farmers are generally recognized as being risk averse. Ostensibly, risk could have some influence on farmer's supply response through expected utility.

Empirically, risk is measured as the difference between the expected and actual prices, using geometric distributed lags on past prices to measure expected prices (Just). Behrman specified the risk variable to be a moving

T. T. Fu is a Graduate Research Assistant and S. M. Fletcher and J. E. Epperson are Associate Professors, Division of Agricultural Economics, University of Georgia.
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[1]Calculated from U.S. Department of Agriculture, Agricultural Marketing Service, 1953-83.

standard deviation of past prices. Almon (polynomial) distributed lag formulations of risk were employed by Traill and Lin. Their results indicated the importance of including risk variables in supply analyses.

In this study, the Just geometric distributed lag risk model with subjective quadratic risk variables is adopted to estimate the response of acres planted by South Carolina tomato growers. The structural form of the traditional Nerlovian partial adjustment or adaptive expectation dynamic model is used for comparison.[2]

MODELS

Two models were used in this study. One model is the geometric lag structural form of the Nerlovian partial adjustment or Cagan adaptive expectation dynamic model. This form, without a measure of risk, allows a consistent comparison to the Just risk model.[3]

The Nerlovian model can be summarized as follows:

Model I

$$(1) \qquad Y_t = a_0 + a_1 Z^*_{t1} + a_2 Z^*_{t2} + \mathrm{DFWP}_t + e_t,$$

where:

Y_t = decision variable, acreage planted in tomatoes in South Carolina in year t (acres);

$Z^*_{tj} = \alpha \sum_{k=0}^{\infty} (1-\alpha)^k Z_{t-k-1,j}$, $(j=1,2;\ k=0, \ldots, \infty)$ are the decisionmaker's subjective expectations for the mean of tomato gross returns (j=1) and corn gross returns (j=2);

Z_{tj} = tomato gross returns (j=1) and corn gross returns (j=2) in year t, respectively (dollars per acre);

DFWP_t = difference in Florida winter price between years t and t−1 (dollars per cwt); and

e_t = error term, independently identically distributed as $N(0,\sigma^2)$.

A discussion of explanatory variables follows in the section on variables and data.

The second model is Just's risk model for which the risk variables are formed by geometrically weighting returns.

Model II

$$(2) \qquad Y_t = a_0 + a_1 Z^*_{t1} + a_2 Z^*_{t2} + a_3 W^*_{t1} + a_4 W^*_{t2} + a_5 \mathrm{DFWP}_t + e_t,$$

where:

Z^*_{tj}, Z_{tj}, DFWP_t, e_t are defined as before

and

$$W^*_{tj} = \beta \sum_{k=0}^{\infty} (1-\beta)^k (Z_{t-k-1,j} - Z^*_{t-k-1,j})^2$$
$$(j=1,2;\ k=0, \ldots, \infty)$$

are risk variables, the decisionmaker's subjective evaluation of the variance of tomato gross returns (j=1) and corn gross returns (j=2).

The estimating procedure for these models follows the approach taken by Klein, in which the subjective mean and/or variance variables are divided into observable and unobservable parts; that is, equation (1) can be rewritten as:

$$(3) \qquad Y_t = a_0 + a_1 (1-\alpha)^{t-t_0} + a_2 X_{t1} + a_3 X_{t2} + a_4 \mathrm{DFWP}_t + e_t$$

and equation (2) can be rewritten as:

$$(4) \qquad Y_t = a_0 + a_1 (1-\alpha)^{t-t_0} + a_2 X_{t1} + a_3 X_{t2} + a_4 (1-\beta)^{t-t_0} + a_5 W_{t1} + a_6 W_{t2} + a_7 \mathrm{DFWP}_t + e_t,$$

where:

$$X_{tj} = \alpha \sum_{k=0}^{t-t_0-1} (1-\alpha)^k Z_{t-k-1,j}$$
$$(j=1,2),$$

[2]Nerlovian models have been criticized from the viewpoint that they are consistent with "rational expectations" only under special circumstances (Eckstein).

[3]To use the reduced form of the Nerlovian model in the comparison would be inconsistent. In addition, any controversy over the randomness of the dependent variable or the capturing of risk in a lagged dependent variable in the reduced form is avoided by not using this form of the model (Dhrymes; Just). Dhrymes has shown that theoretically the reduced form of the Nerlovian model can be derived from the geometric distributed lag model, the structural form of the Nerlovian model with a declining geometric weighted lag distribution on the adjustment coefficients. Thus, the structural form is a subjective expectation model and is theoretically consistent with the reduced form. The structural form model is used to isolate the risk effect from the Just risk model.

$$W_{tj} = \beta \sum_{k=0}^{t-t_0-1} (1-\beta)^k \{Z_{t-k-1,j} - [(1-\alpha)^{t-t_0-k-1}(m_{t0j})]$$

$$- \alpha \sum_{h=0}^{t-t_0-k-2} (1-\alpha)^h Z_{t-k-h-2,j}\}^2$$

$$(j=1,2),$$

$$M_{t_0j} = \{[\alpha \sum_{i=0}^{t_0-t_h-1} (1-\alpha)^i]^{-1}\} \alpha \sum_{i=0}^{t_0-t_h-1} (1-\alpha)^i Z_{t_0-i-1,j} \quad (j=1,2),$$

t_h = beginning year of presample (historical period) data, $t_h < t_0$,

t_0 = beginning year of sample data,

Z_{tj}, $DFWP_t$ = defined as in equation (1),

$(1-\alpha)^{t-t_0}$ = historical subjective mean of tomato and corn gross returns in year t_0, and

$(1-\beta)^{t-t_0}$ = historical subjective risk associated with tomato and corn gross returns in year t_0.

The coefficients a_1 and a_4 are assumed fixed through the sample period and thus can be treated as unknown parameters. Geometric weighting parameters α and β are generated from a maximum likelihood search procedure developed by Just utilizing presample (historical period) data (t_h, ..., t_0-1). It is assumed that tomato and corn returns have the same values of α and β. The estimates derived from the model using this procedure are consistent and asymptotically efficient.

Three hypotheses tested from this risk model are:

H_1: Decisions are not significantly affected by subjective variance of tomato returns,

H_2: Decisions are not significantly affected by subjective variance of corn returns, and

H_3: Decisions are not significantly affected by Florida winter season tomato prices.

VARIABLES AND DATA

Because of limitations due to degrees of freedom in estimation, the subjective mean and variance variables of yield were not included in the risk model. A complementary way is to combine price and yield into a gross return variable by setting gross return equal to price per unit times yield per acre (U.S. Department of Agriculture, 1962 and 1952-83). Since field corn is the major competing crop for tomatoes in South Carolina, corn gross return was included as one of the explanatory variables in the model. Therefore, the subjective means and variances of tomato and corn gross returns were included in the risk model. The covariance term of risk variables was excluded because of high correlation to variance terms and insignificance in preliminary models.

To market tomatoes in late spring, South Carolina farmers must plant tomatoes by mid February. Growers in Florida are the dominant suppliers of tomatoes prior to this time. Florida growers supply fresh tomatoes during late fall, winter, and early spring. Based on the findings of Wells, Florida tomato prices in January and February were hypothesized to influence price expectations of South Carolina producers of late spring tomatoes, thus, affecting planting decisions. Therefore, the Florida winter price (a weighted average of January and February prices) was introduced in the model as the most recent price information for South Carolina farmers concerning planting decisions (Rose; Florida Crop and Livestock Reporting Service). Empirically, a difference term for Florida winter price, indicating the magnitude of change between the consecutive years, was used in the estimation.

The time span covered in this study was from 1950 to 1982. Due to structural change in United States agriculture in the early 1970'S, the sample was separated into two periods. A turning point occurred between 1970 and 1971 in the supply of South Carolina tomatoes, figures 1 and 2. The two sample periods for model estimation were 1956-70 and 1971-82 with 1950-55 and 1962-70 as the two respective historical periods which were required because of the lag structure of the models.

EMPIRICAL RESULTS

The results of Model I, the structural form of the geometric lag model without risk variables shown in Table 1, provide some important implications concerning the framework for farmers' decisionmaking during the sample period. Three equations were estimated: one for the first sample period (1956-1970), one for the second sample period (1971-82), and one for the whole sample period (1956-1982).

The R-square and F values in the first period of estimation are higher than those in the second period. The R-square for the whole

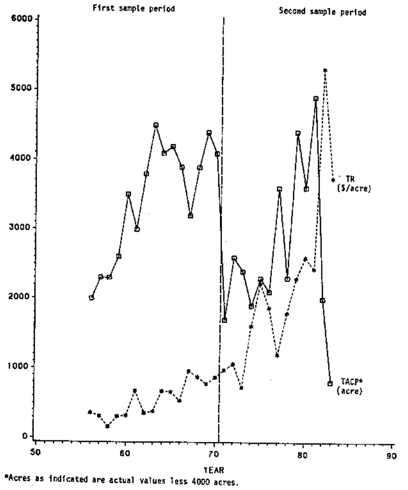

Figure 1. Tomato Acreage Planted (TACP) and Gross Returns (TR) for South Carolina in 1956-82.

period dropped to 0.3067, which indicates the inappropriateness of combining the two periods for estimation. The value of 8.60 for the Chow test of the same regression regime for both periods also indicates that the two periods should not be combined for estimation.

In Table 1, both subjective means of tomato gross returns (Xl) and corn gross returns (X2) have the expected signs, positive for tomato gross returns and negative for corn gross returns, in the first sample period. In this period, the coefficient for the subjective mean of corn gross returns has a high t value. In the second sample period, the coefficient of Xl has a negative sign but is insignificant due to a drastic drop in acreage planted from 1981 to 1982. Florida winter price (DFWP) is the only variable with a coefficient that has a significant t value in the second sample period. However, in the first sample period, the coefficient for DFWP is not significant.

As indicated in the previous section, prices and gross returns are stable in the first sample period and unstable in the second sample period. Thus, the following inferences are plausible. During the stable period, farmers' decisions on acres planted could have largely been based on own prices and prices of competing crops in previous years. However, during the unstable period, previous information on prices appears unreliable. Therefore, farmers seem to try to utilize any recent information available for decisionmaking. Florida winter price (DFWP), representing the most recent information for South Carolina farmers before planting—with a significant t value for the coefficient—indicates its dominant effect on farmers' decisions con-

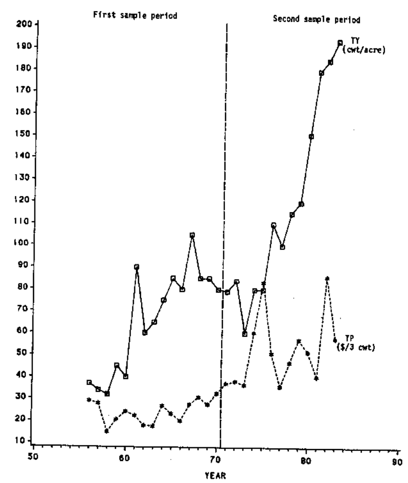

Figure 2. Tomato Prices (TP) and Yields (TY) for South Carolina in 1956-82.

TABLE 1. MAXIMUM LIKELIHOOD COEFFICIENT ESTIMATES FROM MODEL I (WITHOUT RISK VARIABLES) FOR TOMATO ACREAGE PLANTED IN SOUTH CAROLINA, 1956-70, 1971-82, AND 1956-82

Explanatory variables	1956-70		1971-82		1956-82	
	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
Constant	15,974.24	5.93[a]	9,382.28	1.87	7,635.58	21.65[a]
X1[b]	6.56	1.32	−0.06	−0.02	0.27	0.33
X2[c]	−208.52	−3.61[a]	−7.19	−0.14	−7.79	−0.71
$(1-\alpha)^{t-t_0}$[d]	−10,361.38	−2.13[a]	−3,801.76	−0.72	−1,999.42	−2.45[a]
DFWP[e]	1.04	0.04	95.10	4.47[a]	71.88	2.44[a]
R-square	0.82		0.74		0.31	
F-value	11.66		5.08		2.43	
DW value	1.68		1.14		0.95	
MLE α[f]	0.10		0.10		0.44	

[a]Significantly different from zero at 5 percent level.
[b]X1 = subjective mean of tomato gross returns.
[c]X2 = subjective mean of corn gross returns.
[d]$(1-\alpha)^{t-t_0}$ = historical subjective mean for gross returns.
[e]DFWP = Florida winter season tomato price difference.
[f]MLE = maximum likelihood estimate.

cerning acres planted during the unstable period.

Table 2 shows the Just model which includes risk variables in estimation. All the coefficient estimates in Table 2 of subjective means of tomato and corn gross returns have expected signs as in Table 1. For the Just model, a larger variation in tomato gross returns or a higher value of the subjective variance of tomato gross returns would have a negative effect on the planting decisions of tomato growers. Conversely, a larger variance from the competing crop (corn) gross returns would be expected to have a positive effect on tomato planting decisions. Thus, a negative sign was expected for the coefficient of subjective variance of tomato gross returns (W1) and a positive sign was expected for the coefficient of subjective variance of corn gross returns (W2).

Table 2 indicates that the coefficient estimates of the risk variables (W1, W2) have correct signs in both sample periods. Except for W1 in the first period, the risk variables also showed significant effects on the decision variable. These results indicate the importance of risk variables in the supply response model for both the stable and unstable periods.

Given these results, hypotheses one and two can be tested. Hypothesis one (H_1), decisions are not significantly affected by the subjective variance of tomato gross returns, could not be rejected in the first sample period, but was rejected in the second sample period. Hypothesis two (H_2), decisions are not significantly affected by the subjective variance of corn gross returns, was rejected in both periods.

As was the case with Model I, the coefficient for the Florida winter price variable was not significant in the stable (first sample) period for Model II. However, during the unstable period, the coefficient of the variable (DFWP) for Florida winter price was highly significant.[4] Thus, hypothesis three (H_3), decisions are not affected by Florida winter prices, was rejected in the unstable sample period.

TESTS FOR FORECASTING POWER

Both models were used to forecast acreage planted just prior to actual planting. Forecasting was based on all information available just prior to mid February; e.g., the forecast for 1982 was based on Florida winter prices through 1982 and values through 1981 for the other explanatory variables. To evaluate forecasting power, the ratio test of Mean-square-error was employed as a criterion.[5]

As a result of the instability of the explanatory variables, the risk model was expected to have better forecasting ability than the geometric lag structural form model. However, because of structural change, only the equations in the second period can be used

TABLE 2. MAXIMUM LIKELIHOOD COEFFICIENT ESTIMATES FROM MODEL II (WITH RISK VARIABLES) FOR TOMATO ACREAGE PLANTED IN SOUTH CAROLINA, 1956-70 AND 1971-82

Explanatory variables	1956-70		1971-82	
	Coefficient	t-value	Coefficient	t-value
Constant	13,546.260	11.96[a]	5,926.840	7.15[a]
$X1^b$	7.360	4.11[a]	0.912	2.25[a]
$X2^b$	−203.257	−5.20[a]	−4.802	−0.68
$W1^c$	−0.002	−0.70	−0.001	−1.83
$W2^d$	11.782	3.90[a]	0.121	2.65[a]
$(1-\alpha)^{t-t_0^b}$	−13,632.300	−5.95[a]	−706.960	−0.29
$(1-\beta)^{t-t_0^e}$	6,103.214	4.52[a]	504.530	0.27
DFWP[b]	18.646	1.00	110.247	5.20[a]
R-square	0.938		0.804	
F-value	15.060		2.344	
DW value	2.707		1.485	
MLE α^b	0.282		0.658	
MLE β^b	0.463		0.983	

[a]Significantly different from zero at 5 percent significance level.
[b]X1, X2, $(1-\alpha)^{t-t_0}$, DFWP, and MLE are defined in Table 1.
[c]W1 = subjective variance of tomato gross returns.
[d]W2 = subjective variance of corn gross returns.
[e]$(1-\beta)^{t-t_0}$ = historical subjective risk for gross returns.

[4]To use the likelihood ratio test, the null hypothesis (coefficient of DFWP equals zero) could not be rejected at the 5 percent significance level in the first sample period with a calculated value of the likelihood ratio of $\lambda = 0.801$. The null hypothesis was rejected in the second sample period at the 5 percent significance level with $\lambda = 8.641$.

[5]The ratio RMSE/A is often used to compare the forecasts of different models. RMSE is the square root of mean-square error and A is the mean of actual values (Tomek and Robinson).

TABLE 3. COMPARISON OF PREDICTIONS OF TOMATO ACREAGE PLANTED IN SOUTH CAROLINA FROM MODEL I AND II

Year	Actual value	Predicted value	
		Model I	Model II
1981	8,900	11,728.7	11,511.0
1982	6,000	8,320.6	9,137.8
Ratio test (RMSE/A)		0.347	0.387
1983	4,807	7,268.5	−567.4

to forecast the years of the 1980's. Due to the insufficient number of observations in the second period, only three projections can be made for comparison.

As shown in Table 3, Model II predicts better than Model I for 1981, but worse for 1982. In fact, both models failed to predict well for 1982, a year in which supply was reduced sharply. According to the ratio test, Model I had better predictive power during these two years.

The prediction for 1983 was positive from Model I, but it was negative from Model II. The undesirable negative value was caused by an extremely high value for tomato gross returns in 1982, which was 2.2 times the value for tomato gross returns in 1981.[6] The variance term for tomato gross returns in Model II became large after incorporation of the 1982 observation, generating a negative forecast for acreage planted in tomatoes for 1983. The problem lies in the way the distributed lag model captures risk expectations which are formed from previous gross returns. For the 1983 prediction, the model encompasses adjustment coefficients representing risk expectations based on information only through 1981, thus the negative prediction.[7]

CONCLUSION AND IMPLICATIONS

Results from the structural form model indicate the importance of previous price and return information on the planting decisions of South Carolina tomato growers during the stable price and return period (1956-70). Results also point out the dominant effect of Florida winter tomato price as an explanatory variable during the unstable period (1971-82). This seems to imply that farmers would invest in more information with market instability since Florida winter price represents the most recent price information for South Carolina tomato growers before planting.

Risk variables in the Just model appear to be important contributors to an explanation of supply response behavior of South Carolina tomato producers. An increase in risk for tomato gross returns will have a negative effect on the acreage planted of tomatoes in the following year and an increase in risk for corn gross returns will have a positive effect on the decision to plant tomatoes.

The Just risk model predicted better than the Nerlove model for 1981 but it was worse for 1982. Further, the Just risk model predicted negative planted acreage for South Carolina tomatoes for 1983 underscoring the inability of the model to capture a drastic change in risk expectations in the year just prior to the year of forecast. Moreover, neither model performed well, in general, over the 3-year prediction period. Statistically, such forecast performance could be the result of specification error or structural change.

Pope has shown one possible consequence of using aggregate data; that is, an increase in dispersion of expectations would decrease aggregate supply if the supply function is strictly concave. During the unstable price period, the price expectations of individuals could vary widely generating instability of aggregate supply and, thus, increasing the difficulty of forecasting. Schmitz et al. also showed that a multi-product firm would be more likely to prefer price instability in those products that contribute a relatively small proportion to its total revenue. An increasing number of such risk-preferring multi-product firms could also increase the instability of aggregate supply.

Therefore, in order to obtain greater forecasting accuracy, further research should emphasize two aspects. The first is to improve the capability of the expectations component of the models so that all available pertinent information is captured just prior to the forecast period. The second aspect is to find the appropriate disaggregating approaches to distinguish those producers who have different risk attitudes or have extreme expectations of prices.

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[6]U. S. domestic supplies of fresh tomatoes were abnormally low in June and July of 1982 while tomato yields in South Carolina were about average for the same period.

[7]Just risk model was designed to capture slow changes in risk. Thus, extreme changes in gross returns could cause the model to fail (Just, footnote 24).

REFERENCES

Behrman, J. *Supply Response in Underdeveloped Agriculture*, Amsterdam: North-Holland Publishing Company, 1968.

Dhrymes, P. J. *Distributed Lags: Problems of Estimation and Formulation*, San Francisco: Holden-Day, 1971.

Eckstein, Z. "A Rational Expectations Model of Agricultural Supply." *J. Polit. Econ.*, 92(1984): 1-19.

Florida Crop and Livestock Reporting Service. *Florida Agricultural Statistics: Vegetable Summary*, Orlando, 1971-1983.

Just, R. E. "An Investigation of the Importance of Risk in Farmers' Decisions." *Amer. J. Agr. Econ.*, 56,1(1974): 14-25.

Klein, L. R. "The Estimation of Distributed Lags." *Econometrica*, 26(1958): 553-65.

Lin, W. "Measuring Aggregate Supply Response Under Instability." *Amer. J. Agr. Econ.*, 59,5(1977): 903-7.

Pope, R. D. "Supply Response and the Dispersion of Price Expectations." *Amer. J. Agr. Econ.*, 63,2(1981): 161-3.

Rose, G. N. *Tomato Production in Florida: A Historic Series.* Econ. Report 48, Food and Res. Econ. Dept., University of Florida, June, 1973.

Schmitz, A., H. Shalit, and S. J. Turnovsky. "Producer Welfare and the Preference for Price Stability." *Amer. J. Agr. Econ.*, 63,2(1981): 157-60.

Tomek, W. and K. Robinson. *Agricultural Product Prices.* Ithaca, New York: Cornell University Press, 1981.

Traill, W. B. "Risk Variables in Econometric Supply Response Models." *J. Agr. Econ.*, 29,1(1978): 53-61.

U.S. Department of Agriculture, Statistical Reporting Service. *Fresh Market Vegetable Prices*, Washington D.C.: Stat. Bull. No. 318, June, 1962.

_______________. *Vegetables: Annual Summary*, Washington, D.C., 1952-1983.

U.S. Department of Agriculture, Agricultural Marketing Service. *Fresh Fruit and Vegetable Shipments by Commodities, States, and Months*, Washington D.C.: FVUS-7, 1953-1983.

Wells, G. "Forecasting South Carolina Tomato Prices Prior to Planting." *So. J. Agr. Econ.*, 12,1(1980): 109-18.

Young, D. L. "Risk Preferences of Agricultural Producers: Their Use in Extension and Research." *Amer. J. Agr. Econ.*, 61,5(1979): 1,063-70.