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DYNAMIC STOCHASTIC SIMULATION OF DAILY CASH AND FUTURES COTTON PRICES

DeeVon Bailey, B. Wade Brorsen and James W. Richardson

Abstract

A dynamic model of daily cash and futures prices for cotton was developed using time series analysis. The time series model was included in a recursive Monte Carlo simulation model. Validation of the model was performed with a stochastic, dynamic simulation of the estimated model over the observation period 1975-1982 and with a static, deterministic out-of-sample forecast from December 9, 1981 through March 9, 1982. The model was then used to incorporate futures trading strategies into a policy simulation model.

Key words: cotton, forecasting, futures, policy simulation model, time series.

Simulation is becoming an increasingly useful tool for policy analysis at both the macro and micro levels (Salathe et al.; Collins and Taylor; Richardson and Nixon). Although simulation lacks mathematical sophistication and elegance, it is a widely used policy tool because it provides answers to problems that cannot be obtained by other methods (Shannon). Despite widespread use of simulation, sophisticated producer marketing strategies have not been incorporated into farm policy simulation models or into firm growth models. Purcell has suggested that ignoring sophisticated marketing strategies, that depend on commodity futures markets, in policy simulation models may reduce their reliability in predicting producer well-being under alternative farm policies. The objective of this paper is to develop a time series model of daily cash and futures cotton prices and demonstrate how it can be used to incorporate sophisticated marketing strategies in existing policy simulation models.

Numerous studies have investigated forecasting in connection with cash and futures prices. A number of these studies evaluated the ability of current futures prices to forecast future cash

prices (Dole and St. Clair; Martin and Garcia; Just and Rausser). However, Working (p. 14) argued,

"The idea that a futures market should quote different prices for different future dates in accordance with developments anticipated between them cannot be valid when stocks must be carried from one date to another. It involves supposing that the market should act as a forecasting agency rather than as a medium for rational price formation when it cannot do both"

Peck agrees that for storable commodities current futures prices should be most closely related to current cash prices. Similarly, Cunningham argues that distant futures contract prices are simply spreads from the nearby contract price. Thus, all futures contracts should be linked directly to current cash prices for a storable commodity such as cotton.

Leuthold et al., Brandt and Bessler (1981 and 1983) and Rausser and Carter used time series models to forecast cash and futures prices. Even though time series models are dynamic, these researchers were primarily interested in either static or short-run forecasts. Additionally, these researchers were interested in deterministic rather than stochastic forecasts.¹

Helmers incorporated futures prices into a firm level simulation model for a Nebraska grain farm using monthly average futures prices. Inclusion of futures trading strategies in a firm level simulation model would be more appropriately addressed using daily futures and cash prices. The daily price model must be dynamic in nature for this approach to work; thus, time series models of cash and futures prices are a natural choice. A problem with previously estimated time series models of cash and futures prices is that when they are used in a recursive Monte Carlo simulation model, there is nothing to prevent the divergence of cash and futures

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¹A dynamic forecast is obtained when forecasted values are used for the lagged values rather than actual values. A static forecast is obtained when only actual values are used. In a deterministic forecast the error term is assumed to be zero while a random error term is generated for a stochastic forecast. A recursive Monte Carlo simulation is essentially the same thing as a dynamic stochastic forecast.

prices over time. An additional problem faced with time series models is the possibility of negative prices. Furthermore, time series models must overcome the problem that each futures contract lasts for 12 to 18 months while cash prices are continuous.

To overcome some of these difficulties, some pretesting was undertaken in developing a model of daily cash and futures cotton prices. This could be considered a compromise of econometric theory. Thus, evaluation of the resulting model is based on Lehman's argument that a model is valid if it depicts the aspects of the real world it was designed to model. Empirical validation of the time series model for daily cash and futures prices was accomplished in two stages. First, the model was evaluated for its designed purpose, dynamic stochastic simulation. Then, following the example of other researchers (Brandt and Bessler, 1981; Ashley and Granger), the model was evaluated for static deterministic out-of-sample forecasts to demonstrate the model's forecasting ability. Finally, simulated technical trading system returns for the actual data were compared with returns using the same systems in a firm-level simulation model.

THE TIME SERIES MODEL

Modeling daily cash and futures cotton prices ideally involves estimating the multivariate probability density function (pdf) for daily cash and futures prices. However, modeling the multivariate pdf for daily cash prices and several futures contracts is extremely difficult, since estimation of a large number of parameters is required. For example, if normality is assumed, estimation of different means, variances, and covariances for each observation would be required. An alternative to directly estimating the necessary parameters for some a priori pdf is to use time series analysis techniques. Time series techniques attempt to model the underlying stochastic process which generated the original observations.

Both cash and futures cotton prices are expected to be intertemporally correlated since Brorsen and Bailey found that both cash and futures cotton prices took longer than a day to fully adjust to new information. If the autocovariance function of a variable is a combination of both intertemporal decay and truncation (autocovariance becomes zero after p time periods), it may be expressed as an autoregressive moving average model of degrees p and q (ARMA(p,q)) and may be expressed as:

(1)
$$Y^*(t) = \sum_{i=1}^{p} a(i)Y^*(t-i) +$$

$$\sum_{j=1}^{q} b(j)e(t-j) + e(t),$$

where Y' is the dependent variable, a and b are parameter estimates, and e is a white noise error term.

If an ARMA(p,q) process is both stationary and invertible, it may be expressed as an autoregressive process of order infinity $(AR(\infty))$ (Fuller). Since intertemporal correlation is expected to approach zero as the time period between two observations increases, a stationary and invertible ARMA(p,q) process can be approximated by a higher order AR process (Fuller). An AR(p) process may be expressed as follows:

(2)
$$Y^*(t) = \sum_{i=1}^{p} a(i)Y^*(t-i) + e(t)$$
.

Since an AR model can approximate an ARMA process, an AR model was used. The adequacy of the AR model for modeling cash and futures cotton prices is evaluated by testing the residuals for white noise using Bartlett's Kolmogorov-Smirnov test (Bartlett, p. 318). Each futures contract is traded for 18 months, thus, creating overlaps of 6 months at the beginning and end of each contract. To overcome the problem of overlaps, univariate AR models were used and the futures data were analyzed as a single contract. Each contract (March, May, and December) was treated as a separate time series. This corresponds to treating the data as cross section-time series, stretching over 18 months.

The orders of the AR models were determined in two steps. First, the Yule-Walker equations were estimated for each dependent variable using order $p=t,\,t=1,\,2,\,3,\,...,\,30$. The Yule-Walker equations are:

(3)
$$P(k) = \sum_{i=1}^{p} a(i)P(k-i),$$

where P(k) is the autocorrelation function in the current time period. Second, the optimum number of independent variables, and hence the proper number of AR lags was determined using Akaike's Information Criterion (AIC) (Akaike).

When lagged variables are used as regressors, as in an AR model, least squares estimates are biased for small samples (Theil, 1971). However, least squares estimates are asymptotically unbiased and asymptotically efficient if the residuals are uncorrelated and the true model is selected. AIC may overestimate the actual number of lags (Tjostheim). However, in large samples parameter estimates of the variables causing the overspecification will tend to zero thus diminishing, if not totally negating, their effect on the predicted values of the dependent variables (Kmenta).

Data and Modeling Procedure

Data used to estimate the time series model include daily cotton prices from June 15, 1975 to December 1, 1981 for seven futures contracts (18 months each) and corresponding cash prices (USDA). Time series models were developed for cash prices as well as March, May, and December futures contracts. Cash prices were the daily closing quoted price for grade 42, staple 32 cotton at Lubbock, Texas. Prices of cotton futures contracts for March, May, and December delivery were the daily closing prices on the New York futures market for grade 41, staple 34 cotton. These delivery months were chosen because of their frequent use by Lubbock area farmers who hedge their cotton.

As mentioned previously, Working, Peck, and Cunningham have argued that for a storable commodity, such as cotton, futures prices are linked directly to current cash prices. The difference between cash and futures prices is called the basis. These three variables are related by an identity. Thus, if estimates of two of these three variables are obtained, the third can be obtained from the identity. The cash price and the basis are modeled and the futures price is obtained from the identity. This procedure prevents the divergence of cash and futures prices in the simulation process.

Time series analysis assumes the data are mean stationary; i.e., the mean of the data is not a function of time. Cotton prices are not stationary due to time trends caused by inflation and other economic factors. First differences were used to remove any linear time trend in the cash data.

Examination of the periodogram for the first differences of cash cotton prices revealed differences existed for the change in cash price for different days of the week. To correct for this problem, cash differences were standardized by subtracting the mean and dividing by the estimated standard deviation of the price changes for each day of the week. The resulting price series is referred to as the adjusted cash price (ACP). The basis for each futures contract was calculated as the difference between the unadjusted cash price and the futures price. The trend was removed from the basis (BASIS) by regressing the basis on a linear trend as follows (Bowerman and O'Connell):

(4) BASIS_{it} =
$$a_i + b_i t + e_{it}$$
,

where j indicates the contract month (March, May, or December), t is the trend variable, a and b are parameter estimates, and e is the residual error term.

The March, May, and December futures contracts all exhibited significant negative linear trends over the 1975-1981 time period, indi-

cating the local basis has been widening between the beginning and the end of a contract. The ACP and the residuals from equation (4) were tested for seasonal variations using the method outlined by Bowerman and O'Connell:

(5) ACP_t =
$$a + \sum_{L} [b_{L} SIN(2 \pi t/L) + c_{L} COS(2 \pi t/L)] + u_{t}$$

and

(6) RBASIS_{jt} =
$$a + \sum_{L} [b_{L} SIN(2 \pi t/L) + c_{L} COS(2 \pi t/L)] + e_{it}$$

where RBASIS represents the residuals of equation (4) for contract month j, π is approximately 3.14, L is the specified cycle length in days, the u and e are error terms, and SIN and COS represent the sine and cosine functions, respectively.

Periods of the cycles considered were 18, 12, 6, and 3 months. No significant seasonal variation was found for the adjusted cash price. However, significant seasonal cycles were found for the basis residuals of all three contracts. Once the lengths of these cycles were established, the bases were regressed against a linear trend and the appropriate sine and cosine functions. Resulting residuals for the three basis series and the adjusted cash price were assumed to follow as AR process. Adding the significant cycles and the AR lags, the final model was:

(7)
$$ACP_{t} = a + \sum_{i=1}^{p} b ACP_{t-i} + \sigma_{1}$$

and

(8)
$$BASIS_{jt} = a_j + b_j t + \sum_L [c_L SIN(2\pi t/L) + d_L COS(2\pi t/L)] +$$

$$\sum_{i=1}^{q} f_{i}e_{jt-1} + \sigma_{j}, j = 1,3$$

where p and q are lag lengths in the AR processes and σ_j , j=1,3 are white noise error terms. Futures prices for the March, May, and December contracts are estimated by subtracting the estimated basis in equation (8) from the estimated cash price in equation (7).

RESULTS

The four models depicted by equations (7) and (8) were estimated for the adjusted cash prices and the three basis series. The basis series and therefore futures prices were modeled in terms of one continuous contract; however, variances and covariances for the residuals of the nearby basis (final 12 months of each futures contract) and the distant futures basis (first 6 months of each futures contract) were estimated separately. The residuals of equations (7) and

$$\begin{array}{c} \overline{\text{CP}_{t}} = \text{CP}_{t-1} + \text{MCHPC}_{i} + \text{STDCHP}_{i} & (.0027 + .067\text{ACP}_{t-1} - .0385\text{ACP}_{t-2} + .054\text{ACP}_{t-3} + .08\text{ACP}_{t-4} \\ & (-.094) & (2.69)^{\text{``}} & (-1.54) & (2.15)^{\text{``}} & (3.21)^{\text{``}} \\ & + .0376\text{ACP}_{t-5} + .00337\text{ACP}_{t-6} + .0745\text{ACP}_{t-7}) + \delta_{i} \\ & (1.50) & (.135) & (2.98)^{\text{``}} \\ \hline \\ \text{MFP}_{i} = \text{CP}_{t} - [-8.47 - .0074t_{1} - .156\text{Sin}((6.28t_{j})/364) - .624\text{Cos}((6.28t_{j})/364) + .366\text{Sin}((6.28t_{j})/182) \\ & (-51.52)^{\text{``}} & (-13.9)^{\text{``}} & (-1.38) & (-5.45)^{\text{``}} & (3.20)^{\text{``}} \\ \hline \\ & - .623\text{Cos}((6.28t_{j})/182) + .61 \text{ Res}_{\mathcal{B}_{1}}^{(\mathbb{B}_{2})} + .221 \text{ Res}_{\mathcal{B}_{2}}^{(\mathbb{B}_{2})} + .04 \text{ Res}_{\mathcal{B}_{3}}^{(\mathbb{B}_{4})} + \delta_{2} \\ & (5.55)^{\text{``}} & (28.89)^{\text{``}} & (9.02)^{\text{``}} & (4.26)^{\text{``}} & (2.02)^{\text{``}} \\ \hline \\ \hline \\ \text{MYFP}_{t} = \text{CP}_{t} - [-9.70 - .005t_{1} + .55\text{Sin}((6.28t_{j})/546 + .7\text{Cos}((6.28t_{j})/546) + .404\text{Sin}((6.28t_{j})/364) \\ & (-37.39)^{\text{``}} & (-6.43)^{\text{``}} & (2.29)^{\text{``}} & (3.59)^{\text{``}} & (2.09)^{\text{``}} \\ \hline \\ \hline \\ \hline \\ & - .385\text{Cos}((6.28t_{j})/364) + .23\text{Sin}((6.28t_{j})/182) + .512\text{Cos}((6.28t_{j})/182) + .63 \text{ Res}_{\mathcal{B}_{1}}^{(\mathbb{B}_{2})} \\ & - .385\text{Cos}((6.28t_{j})/364) + .23\text{Sin}((6.28t_{j})/182) + .512\text{Cos}((6.28t_{j})/182) + .63 \text{ Res}_{\mathcal{B}_{1}}^{(\mathbb{B}_{2})} \\ & - .16 \text{ Res}_{\mathcal{B}_{2}}^{(\mathbb{B}_{2})} + .097 \text{ Res}_{\mathcal{B}_{3}}^{(\mathbb{B}_{3})} + .03 \text{ Res}_{\mathcal{B}_{3}}^{(\mathbb{B}_{3})} + .05 \text{ Res}_{\mathcal{B}_{3}}^{(\mathbb{B}_{3})} + \delta_{3} \\ & (6.09)^{\text{``}} & (3.79)^{\text{``}} & (1.17) & (2.33)^{\text{``}} \\ \hline \\ \hline \\ \hline \\ DFP_{t} = \text{CP}_{t} - [-8.93 - .002t_{1} + .46\text{Sin}((6.28t_{j})/546 - .98\text{Cos}((6.28t_{j})/546) - .534\text{Sin}((6.28t_{j})/182) \\ & (-7.63)^{\text{``}} & (3.91)^{\text{``}} \\ \hline \\ \hline \\ + .484\text{Cos}((6.28t_{j})/182) + .543 \text{ Res}_{\mathcal{B}_{1}}^{(\mathbb{B}_{1})} + .222 \text{ Res}_{\mathcal{B}_{3}}^{(\mathbb{B}_{2})} + .08 \text{ Res}_{\mathcal{B}_{3}}^{(\mathbb{B}_{4})} + .08 \text{ Res}_{\mathcal{B}_{3}}^{(\mathbb{B}_{4})} \\ & (25.27)^{\text{``}} & (9.13)^{\text{``}} & (5.34)^{\text{``}} & (5.34)^{\text{``}} & (3.74)^{\text{``}} \\ \hline \end{array}$$

t-values for each parameter are in parenthesis below parameter estimate.

bCP_t = cash price in current time period, MCHCP_i = mean change in cash price on the ith day of the week, STDCHP_i = mean standard deviation for change in cash price on the ith day of the week, t_i = trend for the jth futures contract; j = March, May, December, MFP = March futures price, MYFP = May futures price, DFP = December futures price, Res^(k) = Residuals of equation (8) for the kth basis; k = March, May, December, δ_i = error terms; i = 1,2,3,4.

One asterisk denotes significantly different from zero at the 90 percent level while two asterisks denote significant

differences from zero at the 95 percent level.

(8) were used to compute the variance-covariance matrix thus completing estimation of the model needed to simulate daily cotton cash and futures prices. The final form of the model is summarized in Table 1.

The ACP was significantly positively related to its first, fourth, and seventh lags which indicated a relatively slow adjustment for cash prices to new information in the market, Table 1. An AR(4) was selected for the March and December bases, while an AR(5) was selected for the May basis. Bartlett's Kolmogorov-Smirnow test statistics ranged from .012 to .016 for the four models. Since the critical value was .04, the null hypothesis of white noise residuals cannot be rejected.

Model Validation

The purpose of the time series analysis was to model the underlying stochastic process which generated the original observations of cash and futures prices. Since the model was designed to be used in a recursive Monte Carlo simulation model, it was validated through stochastic, dynamic simulation. Although one would not expect the mean and variance of a particular simulation (realization) to equal those of the actual data, the mean of several replications should follow the actual data closely.

The model was dynamically simulated over the estimated period (June 15, 1975 - December 1, 1981) to determine whether the original multivariate probability distribution on cash and futures prices could be recreated. The experiment consisted of 50 stochastic simulations over the 7-year period starting with the same initial values for June 15, 1975. With no price floor imposed on the time series model, the mean annual cash cotton price was much lower than the actual data and the variance was much greater than was actually experienced. When the localized Commodity Credit Corporation's annual loan rates, adjusted for storage and interest, were imposed as a price floor, the model reproduced means and standard deviations much closer to those of the actual data, Table 2.2

The means for the simulated data were not significantly different from those of the actual data at the 90 percent level, based on standard "t" statistics, Table 2. Although all standard deviations were slightly higher for the simulated data, they were found to be statistically equal by both the sign and median tests at the 90 percent level (Freund, pp. 343-347).

The predictive accuracy of the time series model in Table 1 was also evaluated using outof-sample forecasts. Ashley and Granger (p. 376) argue that when model selection is based on the data, post sample validation via forecasting is a necessary check of the model. A static,

²This result indicates the loan rate has had a stabilizing effect on cotton prices in the Lubbock area and should be considered in the time series model as a price floor. It also demonstrates the problems associated with simulating a nonstationary model without consideration for the theoretical or institutional forces in the marketplace.

Table 2. Means $(\bar{\mathbf{X}})$ and Standard Deviations (σ) for Actual and Simulated Data for Cotton Prices

Variable			
and statistic	Actual	Simulated	t ^a
		.	
	Cents	Cents	
Cash:			
X	58.19	59.26	0.674
σ	10.62	11.22	
March nearby:			
X	69.30	70.15	0.518
σ		11.57	
March distant:		11.57	
X	67.67	68.88	0.742
		11.51	0./42
•	9.5/	11.71	
May_nearby:	=0.07	-0.67	0.0/#
X		70.64	0.245
σ	11.49	11.51	
May_distant:			
X	70.97	68.76	-1.381
σ		11.33	-
December nearby:			
X	68.87	68.56	-0.187
σ		11.76	-0.107
December distant:	7./3	11./0	
	15.51	(0.40	1 7/7
X	0.00	68.40	1.747
σ	8.82	11. 5 7	

*t-test for differences in the means.

deterministic, simulation was performed for the period between December 9, 1981 and March 9, 1982. The forecast error measures for this static simulation are presented in Table 3.

Theil's U1 statistic measures forecast accuracy (Theil, 1966). It is bounded by zero and one with a perfect forecast yielding a U1 statistic of zero. The model predicted prices with a high degree of accuracy since U1 approached zero for cash prices and March, May, and December futures prices. Root mean square error (RMSE) is approximately one half of one cent for the futures contracts and one third of one cent for cash price predictions, indicating smaller errors in prediction for cash than for futures prices.

The RMSE can be decomposed into U(bias), U(regression), and U(residual) with these three components summing to one. According to Theil (1966),

"The object is to generate a model with the lowest inequality coefficient possible for each variable; the decomposition should show U(bias) and U(regression)

Table 3. Statistics of Fit and Theil's Forecast Error Measures for Out-of-Sample Simulation, December 9, 1981-March 9, 1982

Variable	Cash	March futures	May futures	December futures
Statistics of fit:				
	0.331035	0.561663	0.545309	0.529963
RMS percent				
errorb	0.006574	0.008692	0.008193	0.007416
Forecast error measures:				
U1	0.0001	0.0001	0.0001	0.0001
U(Bias)		0.00	0.05	0.35
U(Regréssion)	0.06	0.14	0.13	0.05
U(Residual) .	0.93	0.86	0.82	0.60

Root mean square error.

approaching zero and U(residual) approaching one".

The U(residual)'s ranged from .60 for December futures to .93 for cash prices, indicating a relatively high degree of accuracy for the out-of-sample forecasts. The December contract also had the least favorable results in terms of means and standard deviations when comparing actual and dynamically simulated data, Table 2.

These results indicate the time series model should predict daily prices in the future with a relatively high degree of accuracy. Since the model adequately predicts the real world relationship, it is considered to be valid.

Application of Time Series Model

The time series model for generating stochastic daily cash and futures cotton prices was incorporated into a policy simulation model to demonstrate the effects of using technical marketing strategies on the viability of a hypothetical farm under the provisions of the 1981 Farm Bill. The Farm Level Income Tax and Farm Policy Simulator (FLIPSIM V) was modified for this purpose since it is capable of simulating a typical farm over a multiple year planning horizon under uncertain price and yield conditions (Richardson and Nixon). A typical 2,000acre cotton farm in the Lubbock, Texas area was simulated stochastically (50 iterations) over a 10-year planning horizon using technical marketing systems based on stochastic daily cash and futures prices.

The technical marketing systems selected for analysis were a price channel and a dual moving average with a penetration requirement. Pretesting these systems over the actual price data for 1975-1982 indicated a 62-day channel and a 25- and 7-day moving average with a \$0.0025 per pound penetration requirement produced the greatest net returns. This optimization assumed discretionary hedging for one contract of cotton using the March futures contract and no delivery was allowed. The average annual net returns for the 62-day channel were slightly higher and the variability (measured by the coefficient of variation) in annual returns was lower than for the 25/7 day moving average, Table 4. At the 10 percent level, the means of after tax net present value for the 3 market strategies in Table 4 were statistically equal. However, the variance for net present value was statistically greater, at the 10 percent level, under the sell at harvest strategy than the 62-day channel marketing strategy. The variance of net present value for the moving average strategy was not statistically different than the variance for either of the other two strategies at the 10 percent level.

Boot mean square percentage error.

Constant dollars were used in the FLIPSIM model; therefore, the March futures and cash price equations in Table 1 were adjusted to have expected changes of zero. This was done by appropriately changing the intercepts. The period covered by the simulation model was 1983-1992. Since constant prices were assumed, 1983 loan rates and target prices for cotton were used over the entire planning horizon. The initial conditions given the time series model were for December 15, 1982 and normally distributed pseudo random numbers were generated for the daily error terms in the price models. No additional constraints were imposed on the time series model.

The results of simulating the typical farm under the alternative hedging strategies are summarized in Table 4. Both technical hedging strategies assumed the farm operator hedged 50 percent of the expected cotton lint production and stopped all transactions on the futures market after selling the cash crop. The farm's average after-tax net present values for the two strategies differed by only \$1,000; however, they were about \$77,000 greater than if the

TABLE 4. COMPARISON OF MARKETING STRATEGIES USING SIMULATED AND ACTUAL CASH PRICES FOR COTTON IN LUBBOCK, TEXAS AND NEW YORK FUTURES COTTON PRICES

Item	62-day channel	25- and 7-day moving average with ¼¢ penetration	Sell at harvest
	Actual prices 1975-1982		
Net returns from hedge: Mean (\$) Standard	1,090.9	872.5	_
deviation (\$)	4,508.6	5,048.5	_
	Simulated prices 1983-1992 ^b		
After-tax net present valu	ıe:		
Mean (\$1,000) Standard deviation	284.1	285.1	208.8
(\$1,000)	549.1	668.0	841.7
Mean (\$1,000) Standard deviation	737.0	727.5	651.9
(\$1,000)	531.1	647.6_	812.0

*Actual daily cash futures cotton prices for June 15, 1975. December 1, 1981 were used to test the discretionary hedging strategies assuming that one contract of March cotton was traded, the operator could not make delivery, and actual 1982 commission charges and interest rates prevailed over the full-time period.

bA typical farm was simulated stochastically for the selected strategies. For the 62-day channel the farm operator hedged 50 percent of the cotton crop and used a 62-day channel of cash and futures prices to signal transactions in these two markets. The 62-day channel indicated a sell in the cash and/or the futures market if the current closing price was less than any of the preceding 62 closing prices in either of the respective markets. A buy (close the hedge) was initiated in a like manner. Similar rules were assumed for the 25- and 7-day moving average hedging strategy (Bailey). The sell at harvest strategy involves no hedging or use of technical indicators for local cash prices.

operator had sold the cotton at harvest without using the futures market or a technical indicator for cash prices. In addition, the technical hedging strategies significantly reduced the standard deviations for after-tax net present value over the naive marketing strategy. The average net present value for the farm using the channel was higher than with the moving average, Table 4. The standard deviation of the simulated net present values was also lower for the 62-day channel.

SUMMARY AND CONCLUSIONS

Time series analysis was used to identify and estimate AR models to describe the stochastic processes underlying the Lubbock, Texas cash and the New York futures market prices for cotton. Models for the Lubbock, Texas cash price and the March, May, and December bases were estimated and futures prices obtained from the identity relating the basis and cash price. The resulting time series model was used to simulate daily prices for cash and futures markets.

The model was validated using a standard "ttest" to determine whether repeated stochastic, dynamic simulation of the cash and futures prices produced means similar to those of the actual series. Means of the actual and simulated data during the last 7 years were not statistically different. Standard deviations of the actual and simulated data were also not significantly different from one another. An out-of-sample, deterministic, static simulation was also performed. Theil's U1 statistic was small for both the cash and futures prices predictions indicating the model should yield relatively accurate price forecasts for cash and futures cotton prices.

The results from the simulation model indicate no statistical difference in the mean net present value for a farm operator who used a technical hedging strategy versus selling the total crop at harvest. The variance on net present value was, however, statistically lower if the farm operator used a 62-day channel to trigger hedging transactions. These results are consistent with the intended purpose of hedging; that is, a tool for reducing price and/or income risk and not necessarily a method for increasing expected income.

Distributions for generating random crop prices in farm growth and farm policy simulation models have in the past produced only annual or monthly values. Thus, researchers evaluating farm policy and/or farm growth have been unable to simulate the benefits and costs of alternative farm policies for producers who use sophisticated marketing strategies. The time series model for cash and futures prices devel-

oped and demonstrated in this paper allows one to simulate stochastic daily cash and futures prices for cotton. Thus, this model allows firm level simulation models to account for possible transfer of risk, using futures markets in connection with technical trading strategies.

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