Forecasting Monthly Live-Hog Prices Via Different Models

by

Gopal Naik and Raymond M. Leuthold

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INTRODUCTION

At the 1983 price analysis seminar, John Ikerd suggested that instead of forecasting farm-level livestock prices directly as many of us do, these forecasts should be derived from forecasts of retail meat prices. He argued that this seems logical since the demand for livestock is derived from retail meat demand. Spreads between retail and farm-level prices may vary widely on a monthly basis depending on the demand for and supply of marketing services and have considerable influence on the farm-level price relationships. Thus, farm-level prices may be more accurately forecast with a model reflecting both retail demand and the supply of and demand for marketing services. Ikerd then developed a simultaneous system representing intermarket relationships and estimated this conceptual model for cattle. In the 1984 price analysis seminar, he stressed the need for obtaining estimates of the spread to forecast live cattle prices and showed that it is possible to forecast quite accurately the seasonal pattern of the farm-retail price spread for beef. However, from the forecasting viewpoint the suggested methodology is useful only if it outperforms the other alternative techniques of forecasting. Conceptually, forecasting retail price and spread could double the possible sources of error, require more information, and involve greater cost in computation.

This paper examines the hypothesis that farm-level price forecasts are more accurate if derived from a retail-spread model than if they are generated directly for the case of hogs. A 5-equation simultaneous system

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reflecting retail pork demand and the farm-retail price spread is developed. This system is conceptually similar to that suggested by Ikerd in 1983 for cattle, and incorporates monthly data. In addition, a modified simultaneous recursive model and three price dependent single equation models are constructed. Forecasts from these five different models are then compared.

FORECASTING MODELS

Simultaneous Model

Considering that the demand for live hogs is derived from the retail pork market, a system of equations representing both retail and farm levels and their interrelationship is specified as follows:

$$PR_t = f(QRD_t, INC_t, BEEFCNS_t, BROLCNS_t, DV) \quad (1)$$

$$QCURPR_t = f(PF_t, SF_{t-6}, PCORN_{t-10}, R_{t-6}, DV) \quad (2)$$

$$SPREAD_t = f(QCURPR_t, PR_t, W_t, DV) \quad (3)$$

$$PF_t = 0.59*PR_t - SPREAD_t \quad (4)$$

$$QRD_t = QCURPR_t - CCLDS_t \quad (5)$$

where

PR_t = Retail price of pork (cents/lb.) undeflated

QRD_t = Quantity of pork consumption (million lbs.)

$BEEFCNS_t$ = Quantity of beef consumption (million lbs.)

$BROLCNS_t$ = Quantity of broiler consumption(million lbs.)

INC_t = Percapita income ($) undeflated

$QCURPR_t$ = Quantity of current production of pork (million lbs.)

SF_{t-6} = Sow farrowings lagged 6 months(million head)

$PCORN_{t-10}$ = Price of corn lagged 10 months($/bushel)

R_{t-6} = Prime interest rate lagged 6 months

W_t = Wages of meat processing plants($/week) undeflated

PF_t = Farm price of hogs(cents/lb.) undeflated

$SPREAD_t$ = Difference between the liveweight equivalent of the retail and farm price(cents/lb) undeflated

$CCLDS_t$ = Change in cold storage of pork(1000 lbs.)

DV = Monthly dummy variables.

The first equation is a retail-level price dependent demand equation for pork, with quantity of pork consumption, percapita income, quantities of beef and broiler consumption as explanatory variables. The monthly dummy variables are included to account for seasonal fluctuations in demand and thus in the price. In the second equation, farm supply is assumed to be affected by sow farrowings and interest rate six months previous, a period of major production decisions. The lag of the price of corn is also an important production decision variable, and the ten-month lag is determined after a brief search of the data. This reflects the period of breeding decisions. The current farm price of hogs is included to reflect short-run marketing decisions. Monthly dummy variables are included to account for seasonal fluctuations.

The third equation is a spread equation which connects the retail and farm-level prices and reflects the demand for and supply of marketing services through the inclusion of the retail price, quantity of current production and wage rate in meat processing plants as right hand side variables. The seasonality in the supply of and demand for marketing services, strongly argued for by Ikerd(1983), is accounted for by monthly dummy variables. The first identity shows that the spread is the difference between the retail price adjusted equivalent to the liveweight and the farm price for the same month. In the second identity it is assumed that the imports and exports are negligible, and the retail demand is met from current production and stocks. Retail price of pork, quantity of current production of pork, farm-retail price spread, quantity of pork consumption nd farm price of hogs are the five endogenous variables in this system. The system will be referred to as SIM in further discussions.

A modified version of the above system of equations is specified by excluding the farm price from equation(2), which gives a recursive model often found in the literature. This assumes that the production of pork is independent of the current price of hogs. This model will be referred to as MSIM for further reference.

We also obtain an OLS estimation of the MSIM model to generate price forecasts. These forecasts will be referred to as those from model PRSPR.

Single Equation Models

Three alternative price dependent single equation models for live hog prices, that can be easily comprehended, are also specified. They are as follows:

$$PF_t = f(INC_t, QCURPR_t, QCBF_t, BSL_t, DV) \quad (6)$$

$$PF_t = f(INC_t, QCURPR_t, DV) \quad (7)$$

$$PF_t = f(QCURPR_t, PR_t, W_t, DV) \quad (8)$$

where

PF_t = Farm price of hogs(cents/lb.) undeflated

$QCBF_t$ = Quantity of current production of beef(million lbs.)

BSL_t = Broiler slaughter(million lbs.)

and other notations are as previously defined.

Equation (6) is a replica of the retail demand equation used in the above system of equations, but specified as a farm level demand equation. Percapita income, quantity of current production of pork and beef, quantity of broiler slaughter and monthly dummy variables are the explanatory variables. Percapita income has an indirect effect that basically comes from retail demand. In the second equation, equation (7), percapita income and quantity of current production of pork are assumed to have the greatest impact on the live hog prices. The current production of beef and quantity of broiler slaughter are omitted from this equation because of the perceived difficulty in forecasting them. In the above two equations there is an implicit assumption that the spread does not vary due either to seasonality or to changes in the demand for or supply of marketing services. This seems unreasonable from the point of view of Ikerd's hypothesis. So, an attempt has been made to incorporate the supply of and demand for marketing services in the third equation, equation (8). The retail price and wage rate variables are included for this purpose as explanatory variables along with pork production and dummy variables.

Exogenous Variable Forecasts

Predicted values of the exogenous variables are needed when generating forecasts of the endogenous variables. The exogenous variables such as percapita income, broiler slaughter, broiler consumption and wage rate are predicted using trend and dummy variables. These forecasting models look like:

$$Y_{ti} = a_i + b_{1i}T + b_{2i}DV_1 + \ldots\ldots + b_{12i}DV_{11} + e_{ti}$$

where Y_{ti} is the variable being forecasted and T is trend.

The quantity of beef consumption(BEEFCNS) is obtained using the identity:

$$BEEFCNS_t = QCBF_t - CCSB_t$$

where $CCSB_t$ = Change in cold storage of beef(1000 lbs). The quantity of the current production of beef is in turn predicted by regressing it on cattle placed on feed, price of feeder steers and prime interest rate prevailing 6 months before, and dummy variables. The change in cold storage of beef and pork are predicted by regressing each on their immediate past values and monthly dummy variables.

Time-Series Models

Time-series models are specified not only for live hog prices but also for the retail price of pork and the price spread. The forecasts of the retail price of pork and spread are used to compute the live hog price forecasts using the identity:

$$PF_t = 0.59 * PR_t - SPREAD_t. \qquad (9)$$

This forecast of the live hog price will be referred to as TS1, while the forecast obtained by applying time series directly on live hog prices will be denoted as TS2.

The live hog prices, retail price of pork, and spread displayed a constant ARIMA process throughout the entire period of analysis. The ARIMA process identified for each is reported in Table 1.

Table 1. ARIMA Processes Identified for Live Hog Prices, Retail Price of Pork and Price Spread

Prices	Differencing	Autoregression	Moving Average	Seasonal Autoregression	Seasonal Moving Average
Price of hogs	1		1	1	
Price of pork	1	1		1	
Price spread	1	2	1		

ESTIMATION PROCEDURE

The system of equations SIM and MSIM are estimated by a systems estimator, two-stage least squares. MSIM is also estimated by ordinary least squares. A system of equations is expected to reflect the degree of the interdependence among the different equations present in the system.

Autocorrelation is noticed in all the models including the models used for predicting the exogenous variables. Correction for first order autocorrelation is done using Durbin's method. Here, the autocorrelation coefficient is first estimated by regressing the endogenous variable on its lagged value, and current and lag values of exogenous variables. The estimated autocorrelation coefficient is then used to tranform the data on all the variables in the model. The final estimation of the model is done using the tranformed data. In the case of simultaneous system, an augmented reduced form is obtained, as suggested by Kmenta(1971,pp.587-89), before using Durbin's method.

The forecasts from the simultaneous system are generated from restricted reduced form as follows:

$$Y = - \Gamma^{-1} B X \tag{10}$$

Y is the matrix of endogenous variables

X is the matrix of predetermined variables(actual or predicted)

Γ is the matrix of estimated coefficients of endogenous variables

B is the matrix of estimated coefficients of exogenous varaibles.

Data and Forecast Procedure

Monthly data are used for the analysis from January 1974 through December 1984. Most of the data are collected from <u>Livestock and Meat Statistics</u> published annually by the USDA. Income and population come from the <u>Survey of Current Business</u> by the Department of Commerce. Broiler data come from the USDA's <u>Poultry and Egg Situation</u>. Wage rates are published in <u>Employment and Earnings</u>.

Forecasts are made six months beyond the sample period, based on the assumption that the producer makes major production decisions six months before bringing the animals to market. First, the forecasts are generated for January through June 1981 based on data through December 1980. Next, the data used for estimation of the models are updated six months, models reestimated, and forecasts are generated for the subsequent six months. The process is repeated until the last forecast for December 1984. This generates eight sets of forecasts for 1 to 6 months ahead.

For forecasting from the econometric models, the exogenous variables are predicted as described earlier. From the 2SLS estimation of the simultaneous system, restricted reduced form coefficients are obtained and are used for forecasting live hog prices. From the OLS estimation of MSIM retail price and spread are forecasted separately from their respective equations and live hog price is obtained using the identity (9).

The forecasts of live hog prices are also generated from the three farm level single equations after the exogenous variables are predicted. The predicted values of retail price and quantity of current production obtained through OLS estimation of MSIM are used while forecasting the live hog prices from equation (8).

The forecasts obtained after correcting the residuals for autocorrelation using an adjustment procedure suggested by Goldberger(1962) are as follows:

$$y_{t+n} = a + b\, x_{t+n} + \rho^{n}\, e_t \qquad (11)$$

where y_{t+n} is the forecasts of live hogs n periods ahead, a and b are the coefficients obtained after correcting for autocorrelation, x_{t+n} is the actual or predicted values of exogenous variables for peroid `n´, ρ is the estimated autocorrelation coefficient and e_t is the residual at time t.

For the simultaneous system the residuals are suitably transformed before adjustment as follows:

$$Y = - \Gamma^{-1} B\, X - \Gamma^{-1} E$$

where Y, X, Γ, B are as explained for equation (10), and E is the matrix of error terms for the period `t.´ The matrix of error terms E is obtained by multiplying the estimated residuals of last observation (e_{it}) of each equation with the adjusted autocorrelation coefficients of the corresponding equation(ρ_i^n) as described in equation (11).

Finally, composite forecasts are also obtained for all the forecasts from econometric models in combination with the two time series forecasts, TS1 and TS2. Equal weights are used for forecasts of the econometric and time-series models while obtaining composite forecasts.

Forecast Evaluation

Forecast evaluation is done using both quantitative and qualitative measurements. Percentage Root Mean Squared Error(PRMSE), a quantitative measure, is defined as:

$$PRMSE = \sqrt{\sum_{i=1}^{N}\left(\frac{A_i - P_i}{A_i}\right)^2 \Big/ N}$$

where

A_i = Actual prices for the ith period,

P_i = Predicted price for the ith period,

N = Number of forecasts.

For a qualitative assessment of the forecasts, a 4X4 contingency method as suggested by Naik and Leuthold (1985) is used and the ratio of worst forecast to accurate forecast (RWAF) is calculated[1]. Lower values of PRMSE and the ratio of worst to accurate forecasts reflect more accurate forecasts.

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[1] Number of accurate forecasts is the sum of diagonal elements in a 4X4 contingency table, and number of worst forecasts is the sum of elements representing opposite movements of forecasts compared to the direction of movements of actual values.

RESULTS

The estimated coefficents for the SIM model have, in general, expected signs (see Appendix I for one estimation). In the retail price equation, all non-dummy variables are significant at the 95 percent probability level after correcting for autocorrelation and have the correct signs except for quantity of beef and broiler consumption. Before correcting for autocorrelation beef consumption has correct sign but is not significant. The dummy variables display a seasonal pattern in retail price. The coefficients of non-dummy variables in the quantity of current production equation have the expected signs except for prime rate and all are significantly different from zero at the 95 percent probability level. However, after correcting for autocorrelation the farm price of hogs has negative sign and corn becomes insignificant. The seasonal pattern is not very pronounced, especially after correcting for autocorrelation. In the spread equation, the non-dummy variables have expected sign and significant coefficients after correcting for autocorrelation, where as before autocorrection the wage rate has a negative sign and is insignificant. The coefficients for the dummy variables suggest that there is no seasonality according to calendar months, a result opposite the earlier hypothesis. The coefficients estimated for the MSIM model both by 2SLS and OLS have signs and significance levels similar to the 2SLS estimation of the SIM model both before and after autocorrection. However, the DW is lower for the OLS estimation of the retail price equation compared to that obtained by 2SLS before correcting for autocorrelation. There was evidence of second order autocorrelation in all cases for the retail price equation.

The non-dummy variables are all significant at the 90 percent level and have expected signs in all three farm-level single equation models after correcting for autocorrelation (See Appendix II for one estimation of each).

Before correcting for autocorrelation the quantity of current production of beef has a negative sign but is insignicant at the 95 percent probability level for equation (6). There is no evidence of strong second order autocorrelation in any of these equations.

Table 2 presents the evaluation of the forecasts from the alternative methods. Table 2 shows that before correcting for autorrelation the system of equations (SIM) estimated by 2SLS is superior to the other econometric techniques in predicting live hog prices both in terms of PRMSE and ratio of worst to accurate forecasts (RWAF). The forecasts obtained from the 2SLS estimation of MSIM are the worst, having the highest PRMSE (19.14) and RWAF (0.55).

Among the farm-level single equations, equation (7) did best in terms of PRMSE and equation (8) in terms of RWAF. The forecasts obtained from equation (8) are exactly the same as those obtained from the OLS estimation of system (MSIM). This is because these two models include same variables. For further analysis these two will be treated as one forecast.

After correcting for autocorrelation PRMSE is lower in all the cases (Table 2). The gain in accuracy is highest for the models estimated by OLS. This is probably because the autocorrelation correction procedures are more efficient for a single equation than for a system of equations. Though the PRMSE has decreased, the RWAF has increased considerably after correcting for autocorrelation in all individual model cases except farm level equation (7). Time-series models are more accurate in terms of PRMSE when compared with forecasts obtained from econometric models before correcting for autocorrelation. However, after correcting for autocorrelation the time series and econometric models are very comparable in forecasting accuracy. The forecasts obtained from directly applying time series to live hog prices

Table 2: PRMSE and RWAF for Different Forecasting Techniques

	SIM	MSIM	PRSPR	PF(6)	PF(7)	PF(8)	TS1	TS2	FP
INDIVIDUAL MODELS of Forecasts									
Before Auto-correction									
PRMSE	15.85	19.14	17.87	18.42	16.07	17.87			
RWAF	.4762	.5500	.4762	.5263	.5263	.4762			
After Auto-correction									
PRMSE	14.47	13.45	12.44	13.70	10.77	12.44			
RWAF	.8460	.8570	.6250	.7333	.4118	.6250			
Time Series									
PRMSE							12.21	12.81	
RWAF							.7143	.2500	
Futures									
RMSE									12.59
COMPOSITE									
Using TS1									
Before Auto-correction									
PRMSE	11.66	12.71	12.11	12.53	11.58	12.11			
RWAF	.5882	.7059	.5000	.5263	.5263	.5000			
After Auto-correction									
PRMSE	11.01	10.65	10.28	11.12	10.00	10.28			
RWAF	.8462	.8462	.5000	.6110	.3000	.5000			
Using TS2									
Before Auto-correction									
PRMSE	12.29	13.57	13.03	13.29	12.43	13.03			
RWAF	.4000	.4000	.4000	.4736	.3684	.4000			
After Auto-correction									
PRMSE	12.20	11.80	11.20	11.81	10.88	11.20			
RWAF	.7330	.5000	.5330	.4110	.5000	.5330			

Table 2 continued

Key

SIM = Forecast obtained from 2SLS estimation of equations

MSIM = Forecast obtained from 2SLS estimation of modified specification of the system

PRSPR = Forecast obtained from OLS estimation of MSIM specification

PF(6) = Forecast obtained from farm level equation(6)

PF(7) = Forecast obtained from farm level equation(7)

Pf(8) = Forecast obtained from farm level equation(8)

TS1 = Forecast obtained from applying time series on retail price and spread

TS2 = Forecast obtained from applying time series directly on live hog prices

FP = Futures price

(TS2) are superior to TS1 in terms of RWAF. For comparison, futures prices as forecasts are also evaluated, and their PRMSE is within the range established by the econometric and time-series models after correcting for autocorrelation.

The composite forecasts obtained using time-series model TS1 performed better than those obtained using forecasts from TS2 in terms of PRMSE. The RWAF is smaller for those forecasts obtained using TS2 in all cases except for the forecasts of equations (7) and (8) after correcting for autocorrelation. In terms of PRMSE the composite forecasts obtained from a single farm-level equation (7) are usually the most accurate. This model performed better than those models that account for the demand for and supply of marketing services except for individual forecasts before correcting for autocorrelation. The RWAF also shows that in three out of the six cases equation (7) performed best, and in other cases it was close to the best. Overall, the forecasts from equation (7) outperformed other models, suggesting that it is not necessary to take into consideration the demand for and supply of marketing services while forecasting live hog prices.

Another striking feature is that after correcting for autocorrelation the OLS estimation of MSIM performed better than 2SLS estimation of either SIM or MSIM, and the forecasts are close to the ones obtained from equation (7).

A test suggested by Brandt and Bessler(1981) is used to see whether the mean squared errors(MSEs) of different models differ significantly from each other. Applying that test here, the MSEs of SIM and single farm-level equation (7) were found to be equal at the 5 percent significance before correcting for autocorrelation, and were not equal after correcting for autocorrelation. For composite forecasts obtained using TS2, the results were similar. However, the MSEs of those two models were equal for composite forecasts obtained using TS1 both before and after correcting for autocorrelation. The MSEs of single farm-level equation (7) before and after correcting for autocorrelation were not equal for both the composite forecasts. These results support the observations made hitherto.

Due to the fact that the single farm-level equation (7), which performed best, does not include the substitutes, and the substitutes had wrong signs in simultaneous equations, the models SIM, MSIM and PRSPR were reestimated excluding the substitutes to see whether the forecasts performed better. The result showed that the SIM model forecasts obtained before correcting for autocorrelation were slightly better, but worse after correcting for autocorrelation, compared to the earlier forecasts. There was slight improvement in the forecasts for model PRSPR in all the cases but not significant enough to outperform the forecast from farm-level equation (7). For MSIM model the results were mixed. This reestimation did not, in general, give improved performance.

SUMMARY AND CONCLUSIONS

This analysis shows that autocorrelation needs to be taken into account before forecasting live hog prices. Forecasting live hog prices through the system of equations which includes retail demand and spread equations performs better than the three single equation models at the farm level before correcting for autocorrelation, but worse after correcting for autocorrelation. Forecasts of all models improve after correcting for autocorrelation.

For the time-series models, the PRMSE shows that it is better to obtain the live hog price forecasts from the forecasts of retail price and spread than from the model applied directly to live hog price. However, utilizing the RWAF measure it is better to obtain farm-level price forecasts directly from applying time series to live hog prices.

Forecasts obtained from the farm-level single equation (7) after autocorrelation is corrected are the most accurate among all the forecast in terms of PRMSE, and forecasts obtained from direct application of time series to live hog prices (TS2) are most accurate in terms of RWAF. Equation (7) includes only quantity of current production and percapita income as explanatory variables along with dummy variables.

Based on the PRMSE measure composite forecasts are more accurate than either the time series or econometric forecasts. Among the composite forecasts, the set obtained using the forecasts from TS1 performed better in terms of PRMSE and from TS2 in terms of RWAF.

The results show that for the hog sector the model which incorporates retail demand and price spread does not outperform the single equation farm-level forecasts. With a simple farm-level equation it is possible to forecast the live hog prices more accurately than with a complicated simultaneous system. However, correction for autocorrelation is essential while using econometric models for forecasting, especially to increase the quantitative accuracy of forecasts.

Thus, the method suggested by Ikerd for obtaining price forecasts from the retail level and price spread not only requires more information and is more complex to compute, but it is less accurate in predicting monthly prices of hogs in our case. That is, his suggestion is more costly both in terms of computation and obtaining required information without substantially improved results. It is possible that a more accurate simultaneous equation forecasting system exists, but it will take further research to discover.

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APPENDIX I: Coefficients Estimated for Simultaneous System for the Period January 1974 through June 1984

Explanatory variables	Before Autocorrection			After Autocorrection		
	PR_t	$QCURPR_t$	$SPREAD_t$	PR_t	$QCURPR_t$	$SPREAD_t$
PR_t			0.36 (9.92)			0.27 (7.66)
$QCURPR_t$			0.026 (4.99)			0.014 (3.25)
PF_t		6.51 (2.86)			-3.18 (-1.67)	
QRD_t	-0.11 (-10.90)[a]			-0.059 (-7.32)		
PCI_t	0.0066 (6.52)			0.0075 (6.15)		
$BEEFCNS_t$	-0.0065 (-0.89)			0.023 (5.31)		
$BROLCNS_t$	29.02 (4.83)			12.37 (2.04)		

Appendix I continued

Explanatory variables	Before Autocorrection			After Autocorrection		
	PR_t	$QCURPR_t$	$SPREAD_t$	PR_t	$QCURPR_t$	$SPREAD_t$
SF_{t-6}		0.54 (10.33)			0.35 (5.73)	
$PCORN_{t-10}$		-40.54 (-1.73)			-37.32 (-1.21)	
R_{t-6}		4.75 (1.69)			11.25 (3.22)	
W_t			-0.012 (-0.61)			0.038 (2.14)
FEB	-9.57 (-2.34)	-116.02 (-3.07)	2.04 (1.46)	-0.48 (-0.39)	-106.32 (-4.12)	1.16 (1.35)
MAR	-0.73 (-0.19)	61.53 (1.62)	-0.25 (-0.18)	0.91 (0.58)	49.21 (1.56)	0.79 (0.74)
APR	-15.08 (-3.53)	50.77 (1.32)	0.69 (0.50)	-5.28 (-2.09)	28.78 (0.85)	1.19 (1.06)
MAY	-15.51 (-3.68)	6.40 (0.17)	0.610 (0.45)	-6.37 (-2.48)	-4.36 (-0.12)	0.54 (0.47)
JUNE	-17.50 (-4.11)	76.22 (1.90)	0.99 (0.72)	-7.32 (-2.81)	26.74 (0.70)	0.16 (0.14)
JULY	-15.74 (-3.59)	-25.34 (-0.62)	2.28 (1.51)	-5.44 (-2.14)	-51.00 (-1.31)	0.68 (0.54)
AUG	-6.20 (-1.51)	44.53 (1.10)	-0.45 (-0.32)	-1.90 (-0.78)	26.48 (0.67)	-0.87 (-0.73)
SEPT	-7.52 (-1.82)	-238.63 (-5.44)	-0.19 (-0.14)	-0.70 (-0.30)	-147.49 (-3.63)	-0.45 (-0.38)
OCT	12.49 (3.14)	-106.24 (-2.49)	-1.59 (-1.08)	6.76 (3.53)	-35.01 (-0.89)	-0.26 (-0.21)
NOV	6.82 (1.74)	-98.33 (-2.36)	1.28 (0.92)	6.19 (3.45)	-54.85 (-1.49)	1.87 (1.76)
DEC	5.27 (1.34)	44.22 (1.14)	0.33 (0.24)	5.22 (3.48)	34.21 (1.27)	0.82 (0.95)
INTERCEPT	129.35 (5.38)	-324.27 (-1.67)	-39.64 (-7.41)	11.379 (3.27)	268.00 (2.38)	-12.30 (-5.50)
R^2	.845	.763	.889	.642	.678	.776
DW	1.22	1.25	.89	.93	2.35	1.51

[a] t-ratio in paranthesis

APPENDIX II: Coefficients Estimated for Farm Level Equations for the Period January 1974 through June 1984

Explanatory variables	Before Autocorrection			After Autocorrection		
	$PF_t(6)$	$PF_t(7)$	$PF_t(8)$	$PF_t(6)$	$PF_t(7)$	$PF_t(8)$
PR_t			0.28 (10.01)			0.34 (10.98)
$QCURPR_t$	-0.052 (-13.3)[a]	-0.043 (-13.0)	-0.022 (-5.75)	-0.028 (-7.04)	-0.017 (-5.07)	-0.011 (-3.64)
PCI_t	0.00047 (0.87)	0.0025 (12.36)		0.0017 (3.19)	0.0015 (4.00)	
$QCBF_t$	-0.0051 (-1.60)			0.011 (3.21)		
BSL_t	0.039 (4.01)			0.010 (1.45)		
W_t			-0.011 (-0.78)			-0.048 (-3.31)
FEB	-3.27 (-1.74)	-3.89 (-2.12)	-1.80 (-1.34)	0.44 (0.435)	-1.08 (-1.05)	-1.14 (-1.28)
MAR	0.71 (0.42)	0.73 (0.40)	-0.15 (-0.11)	0.58 (0.48)	-0.80 (-0.64)	-1.08 (-1.01)
APR	-2.90 (-1.61)	-1.22 (-0.68)	-0.84 (-0.64)	-0.13 (-0.088)	-2.22 (-1.57)	-1.39 (-1.24)
MAY	-4.82 (-2.58)	-1.81 (-1.01)	-0.56 (-0.43)	-1.23 (-0.79)	-1.78 (-1.18)	-0.66 (-0.57)
JUNE	-6.31 (-3.33)	-3.17 (-1.75)	-0.70 (-0.52)	-1.71 (-1.07)	-1.34 (-0.85)	-0.19 (-0.16)
JULY	-7.20 (-3.60)	-4.16 (-2.19)	-1.83 (-1.28)	-1.29 (-0.77)	-0.62 (-0.37)	-0.67 (-0.54)
AUG	-2.59 (-1.39)	0.048 (0.02)	0.482 (0.355)	0.34 (0.22)	1.60 (0.99)	0.73 (0.61)
SEPT	-0.21 (-0.12)	0.72 (0.39)	0.20 (0.15)	1.02 (0.92)	1.28 (0.83)	0.30 (0.26)
OCT	3.80 (2.13)	3.82 (2.05)	1.04 (0.74)	1.41 (1.04)	1.37 (0.94)	-0.12 (-0.10)
NOV	4.11 (2.05)	0.28 (0.15)	-1.49 (-1.09)	0.86 (0.61)	-1.77 (-1.38)	-2.10 (-1.97)
DEC	2.69 (1.457	0.28 (0.15)	-0.53 (-0.39)	0.97 (0.97)	-0.83 (-0.86)	-1.05 (-1.20)
INTERCEPT	78.34 (9.49)	74.01 (21.88)	33.81 (8.32)	10.19 (5.18)	14.85 (11.10)	13.06 (5.94)
R^2	.706	.662	.797	.474	.370	.726
DW	0.97	0.87	.80	1.40	1.39	2.72

[a] t-ratio in paranthesis