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THE CORN-EGG PRICE TRANSMISSION MECHANISM

Ronald A. Babula and David A. Bessler

Abstract

A vector autoregression (VAR) model of corn, farm egg, and retail egg prices is estimated and shocked with a corn price increase. Impulse responses in egg prices, t-statistics for the impulse responses, and decompositions of forecast error variance are presented. Analyses of results provide insights on the corn/egg price transmission mechanism and on how corn price shocks pulsate through the egg-related economy.

Key words: corn/egg price transmissions, vector autoregression, impulse responses, Chow test, forecast error variance decompositions, Kloeck-Van Dijk Monte Carlo procedure

This paper employs vector autoregression (VAR) econometrics to identify empirical regularities between corn and egg prices and uses the regularities to demonstrate how these prices have dynamically interacted since the 1950s. Recent research has used time series techniques to monitor policy-relevant dynamics on how farm sector shocks, which work through crop prices, influence related food prices in the economy's noncrop sectors. Babula and Bessler (1989b) employed vector autoregression methods to reveal the dynamic characteristics or attributes of how a farm sector shock, which changes farmgate wheat price, pulsates through the nonfarm economy as price changes for wheat-based goods. Babula, Bessler, and Schluter (1990) used VAR techniques to examine the dynamic relationships among corn price, farm poultry price, and retail poultry price, and how these relationships have changed over the 1957-1989 period. This previous research has focused on the following dynamic attributes concerning how related noncrop prices respond to a

change in farm crop price: (1) reaction times for responses, (2) directions, patterns, and durations of responses, (3) how response patterns for related prices are similar (or dissimilar) across sectors, and (4) the strengths of the interrelationships among crop-related prices in different sectors of the economy.¹

In this paper, VAR econometrics is used to identify empirical regularities from monthly time-ordered data on how farm corn price (PCN), farm-level egg price (PF), and retail egg price (PR) have dynamically moved together and interacted together through time. More specifically, this paper uses VAR econometrics to describe the dynamic attributes listed above in items (1) through (4) for the PCN-PF-PR price transmission.

The paper is presented in five additional sections. First, a digression on VAR modeling is presented. This section provides a justification for use of VARs with uncontrolled secondary data. Second, the data sources are described and a brief summary of the estimated model is given. At the paper's focus is the dynamic relationship among the three series under investigation, and because these dynamics are best described in their moving average (impulse response function) form, rather than in their autoregressive form (Sims 1980), the estimated autoregressive model is not presented. The stationarity of the residuals from the autoregressive representation and out-of-sample forecasts from the estimated VAR is considered as additional evidence on the appropriateness of the estimated VAR. The third section of the paper presents the impulse response functions that are derived from the autoregressive representation. This section is followed by an analysis of forecast error variance decompositions, which measure the strength of dynamic inter-

¹Some VAR econometric work on egg prices has appeared: Shrader, Bessler, and Preston (1985); Bessler and Shrader (1980); and Thurman and Fisher (1988). Thurman and Fisher (1988) examine causality relationships between annual egg and chicken prices. The other two studies are time series comparisons of competing daily egg quotes at one point in the food chain. The study reported here is different, in that it uses monthly data to examine egg-related price effects of a farm sector shock that influences corn price.

Ronald A. Babula is an Agricultural Economist with the National Aggregate Analysis Section, Economic Research Service, U.S. Department of Agriculture. David A. Bessler is a Professor of Agricultural Economics, Texas A&M. University. The authors wish to thank Dr. Gerald Schluter, Leader, National Aggregate Analysis Section, Economic Research Service, for input and suggestions in all phases of this study, and Dr. Dan McLemore and three anonymous reviewers for their helpful comments. The opinions herein are the authors' and not necessarily shared by the U.S. Department of Agriculture or Texas A&M.

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relationships among the three price series. A final section provides conclusions.

A DIGRESSION ON THE VAR MODEL'S SPECIFICATION

Certain aspects of VAR model specification have generated criticism among some economists (see Sims 1989). Some contend that the number of included variables and lags are determined in too mechanical a manner, without enough attention to theory. Another criticism has been that modeling efforts have not employed economic theory in an intensive enough manner, as when formulating the Choleski ordering of the VAR's variables in contemporaneous time.

One cannot expect economics to differ from other disciplines and be exempt from having an expanding choice of different model types with varying levels of detail for different purposes (Sims 1989). "It is dismaying... that as economists begin to use an increasingly differentiated array of modeling types, we seem to be dissipating energy in argument over what kind of modeling style is correct" (Sims 1989, p. 489). Sims (1989) further contends that meaningful modeling efforts in economics range along a wide spectrum: from unrestricted and data-oriented VAR models which loosely use theory to purely theoretical models with little or no connection to observed data or events. One chooses a modeling effort along this spectrum by using, as does this study, model choice criteria presented by individuals such as Sims (1989) and Friedman (1953).

An ideal, but seldom achieved, model would (a) incorporate explicit behavioral theory, (b) connect to the data, (c) permit acceptably high confidence levels for tests of hypotheses and inferences, (d) have a specification partially guided by the analytical purpose at hand, and (e) predict accurately beyond the sample (Friedman 1953; Sims 1989). Any particular model is a compromise and no model can be expected to meet all five of these criteria perfectly (Sims 1989, p. 489). VAR models typically adhere to criteria (b), (d), and (e), while often sacrificing much with regard to criteria (a) and (c). Reasons may vary from study to study, but prime among such reasons is the uncontrolled nature of the data generating process. Most VAR applications are

with secondary data in which no control is made for omitted variables. That is, there is usually not a random assignment of independent variables, so that one is never sure that the error terms are not correlated with the independent variables. Thus, usual hypothesis tests and inferences on structure will be subject to question (Rubin 1978). Accordingly, rather than seeking a close link with *a priori* theoretical structure with the data, some VAR modelers (see Bessler 1990) choose to obtain a summary of regularities present in the data which have good forecasting characteristics. This study follows this latter data-oriented and a theoretic approach. (For a detailed discussion on the role of randomization and control in obtaining structure, the reader is referred to Rubin 1978, and Pratt and Schlaifer 1988).

DATA SOURCES AND THE ESTIMATED VAR MODEL

The data used in this study are monthly time series observations obtained from the U.S. Bureau of Labor Statistics (BLS).² The BLS's producer price index (PPI), farm products, corn no. 2, Chicago, was chosen to represent the corn price near the farmgate (PCN). The PPI, farm products, eggs, serves as the farm-level egg price (PF).³ Retail egg price (PR) is represented by the consumer price index, all urban consumers, eggs. The sample or estimation period spans monthly observations over the years 1957-1989. These data were transformed to natural logarithms. The statistical package, Regression Analysis for Time Series (RATS), generated all VAR econometric results (Doan and Litterman).

Under rather general conditions, a set of theoretically-related time-ordered variables can be summarized as a vector autoregression. Such a model relates current levels of each variable to lags of itself and of every other variable in the system. In the application under study, monthly corn, farm egg, and retail egg prices were each posited as a function of lags of all three variables. Tiao and Box's lag selection method was used to determine lag structure. The Tiao-Box likelihood ratio tests, conducted at Lutkepohl's suggested 1 percent significance level, suggested a 21-order lag on each variable in each of the three VAR relations. Each equation also included a constant, a time trend to account for time-depend-

² Nominal prices were used for two reasons. This is an applied time series analysis, and the public and media focus primarily on nominal movements. Further, a VAR was estimated with deflated prices, and provided results similar to those which emerged from this nominal price model.

³ The BLS failed to record PF values for three months (October, November, and December) in 1983. Approximations for these three observations were obtained through the application of observed percentage changes in the Umer-Barry quotes for the missing months. These three BLS PF-values in 1983 were the only missing values in an otherwise unbroken sample of 396 observations for the 1957:1 through 1989:12 period.

ent influences, and a series of 11 indicator variables to account for seasonal effects.

It is typical to first perform stationarity tests on each of the individual series before the series are analyzed in a vector autoregression (Granger 1981). Nerlove *et al.* (1979), however, suggest that stationarity-inducing transformations be avoided such that the nonstationarity of one series is used to explain the nonstationarity in the others, whereby one may avoid the sacrifice of valuable long-run information through differencing. Individually nonstationarity series may have combinations that are stationary in that they generate stationary residuals (Engle and Granger; Hendry). In such cases, stationary linear combinations of individually nonstationary series may be modeled without differencing, and hence without sacrificing the long-run dynamic information.

Accordingly, it is only the stationarity of the estimated equations that is ultimately required (Sims 1980; Hendry). Thus, focus was placed on testing the stationarity of the innovations from the above-specified 21-order VAR model. Three tests were performed on the residuals of each VAR model equation: a Durbin-Watson (DW) test (Engle and Granger); the Dickey-Fuller (DF) test (Fuller; Dickey and Fuller 1979, 1981); and the augmented Dickey-Fuller (ADF) test (Engle and Granger; Hall). All nine stationarity tests were conducted at the 5 percent significance level.

The DW test for a VAR equation's residuals involves the Durbin-Watson value. The null hypothesis of nonstationary residuals is rejected when the DW value exceeds 0.367 (Hall). Dickey and Fuller (1979, 1981) developed a stationarity test by regressing a variable's (here an equation's residuals) first differences against a one-period lag of the variable's non-differenced levels and a constant. Engle and Granger, and Hall have employed an ADF test. In addition to the DF test's regressors, the ADF test regressors include a number of lagged dependent variables (*i.e.*, lags of the differenced residuals). Hsiao's method of choosing lag structure based on the Akaike final prediction error criterion determined the number of lagged dependent variables in each ADF test. With the DF and ADF tests, the null

hypothesis of a nonstationary series is rejected when the t-like value on the non-differenced lagged variable is negative and exceeds the 2.89 to 3.1 range in absolute value (Fuller; Dickey and Fuller 1979, 1981; Hall).

Evidence from all nine tests was adequate to reject the null hypotheses of nonstationarity for PCN, PF, and PR residuals. The three DW values were approximately 2.0. The three t-like values ranged from 18.9 to 19.1 for the DF tests, and from 13.0 to 13.8 for the ADF tests.

The sample period (1957-1989) was large enough to warrant checking whether there was structural (market and institutional) change as manifested by nonconstant coefficients. As recommended by Sims (1980, p. 17), a Chow test on egg prices for the periods before 1974 and after 1973 was conducted to see whether evidence was sufficient at the 1 percent significance level to suggest that egg price coefficients were nonconstant. Shrader *et al.* fully describe this test's application within an egg price context. Evidence was not sufficient to reject the null hypothesis of coefficient constancy. Accordingly, the VAR model analyses in this paper utilized the entire 1957:1 through 1989:12 period.

The model was validated beyond the sample by estimating a version over the 1957:1 through 1986:12 period, by saving the 36 observations of the 1987:1 through 1989:12 period as an out-of-sample validation period, and by predicting the VAR model version estimated through 1986:12 over the latter validation period. Validation results suggest that the estimated VAR model predicts beyond the sample more accurately than the naive model. This suggests that gains in forecast accuracy have accrued to this study's VAR modeling efforts.⁴ Then the model used for analysis in the remainder of this paper was estimated for the entire 1957:1 through 1989:12 period, which included the three-year validation period.

Two aspects of the 21-order VAR model are of interest. First is the response of variables in the system to a large shock in corn price (for example, one standard error of corn price's historical innovation). In particular, it is of interest to know how farm and retail egg prices, constituting the rest of the

⁴Each equation (initially estimated with 1957:1 through 1986:12 data) generated as many "step-ahead" forecasts as the validation period would allow. The forecasts were run through a Kalman filter. Thus, the 36-month validation period permitted 36 one-step-ahead forecasts; 35 two-step-ahead forecasts; 34 three-step-ahead forecasts, etc. Theil U-statistics were provided for each forecast horizon, that is, 36 Theil U-values for each equation. A Theil U-value of less than unity suggests a superior and more accurate performance that does the naive model. A naive forecast equals last period's observation. Further, a Theil U of less than unity suggests that there were gains in forecast accuracy from modeling the VAR equations as a multivariable system as opposed to expending no model efforts through naive forecasting. Gains to modeling were apparent. Of the farm egg price's 36 Theil U-values, 35 were about unity or less and 31 were about 0.80 or less. Of the 36 retail egg price U-values, all but two were approximately unity or less, and 31 were about 0.80 or less. More than three-fourths of both equations' 36 Theil U-values were 0.75 or less.

modeled system, react over time. Do the responses for egg prices quickly fade out, or do they endure for a long period of time? Do retail prices take longer to respond than do farmgate prices of eggs? If so, how much longer is the delay?

A second aspect of VAR econometrics that is of interest is the relative strength of influence that one variable has on another over alternative time horizons. This is summarized through decompositions of forecast error variance (FEV). For example, consider the retail egg price. Of the uncertainty in retail egg prices at different horizons, what proportion can be attributed to corn price uncertainty? What proportion is attributed to farmgate egg price uncertainty? VAR econometrics can provide helpful information for these questions concerning inter-relationships among all of the modeled prices.

The PCN, PF, and PR equations may have contemporaneously correlated innovations. To avoid distortion of impulse responses from contemporaneously correlated current errors, a Choleski decomposition was imposed in order to orthogonalize the current innovation matrix, such that the variance/covariance matrix of the transformed current innovations is identity. The ordering of farm corn price, to farm-level egg price, to retail egg price was chosen. The ordering provides a line of causality (in contemporaneous time) consistent with theory, because corn price is an input price for farm-level egg output priced by the farm egg price (PF), and because PF is an input price for retail egg products priced by the retail egg price (PR) (See Tomek and Robinson). Further, the PCN-PF-PR ordering is an observed chronology of egg-related pricing points in the food chain. The chosen ordering also facilitates the analytical purpose at hand: to model the dynamic effects on egg-related prices from a crop sector shock to corn price (See Sims 1989).⁵

EGG PRICE IMPULSE RESPONSES TO A RISE IN CORN PRICE

The impulse response function simulates, over time, the effect of a one-time shock in one of a VAR's series on itself and on other series in the system. The VAR was shocked by a 5.6 percent (one standard deviation) rise in the historical innovation in farmgate corn price. The impulse responses are changes in the logged index and are hence approximate percent changes in the non-logged indices.

Figure 1 provides impulse responses in farm- and retail-level egg prices from the increase in corn price. Kloek and Van Dijk's Monte Carlo method was employed and provided t-values for each impulse response. This paper focuses on the first 17 impulses in each egg price because most of these were statistically nonzero at the 1 percent significance level. Thirty-six impulses are provided to demonstrate that the impulse responses implode, rather than explode, at longer term horizons.

Farm egg price or PF increases have an immediate reaction time because the first response to a corn price increase is significant. PF-impulses fluctuate between magnitudes of 1.3 and 2.4 percent for 17 months.

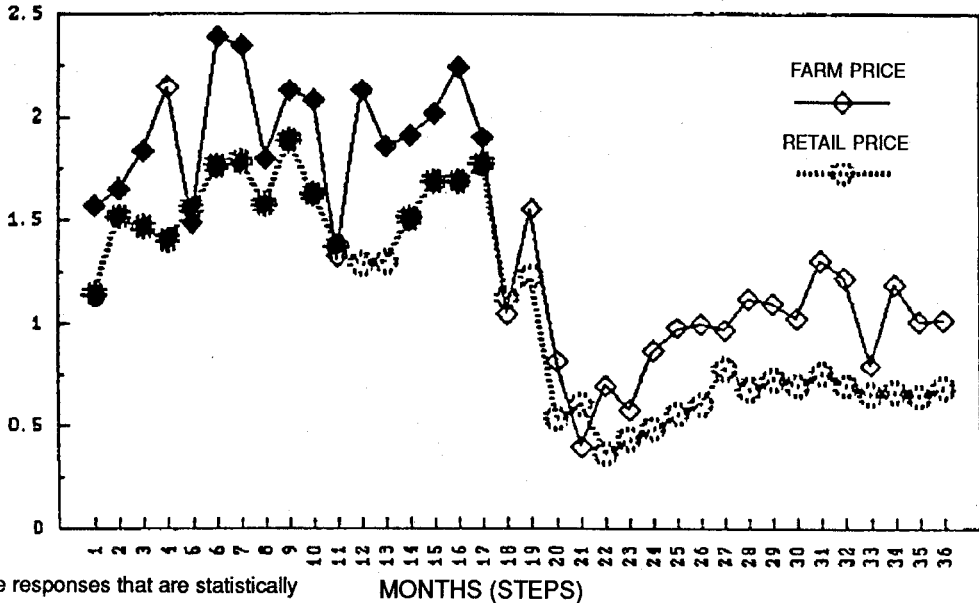
Retail egg price increases also have an immediate reaction time to the PCN-shock. These retail price impulses fluctuate between magnitudes of 1.2 and 1.9 percent and are also statistically nonzero for 17 months.

Patterns of farm and retail responses have immediate reaction times, have the same durations (17 months), and take on similar response patterns. Yet the corn price shock was followed by farm price increases that ranged between 1.3 and 2.4 percent; these were generally higher than the retail price increases which ranged from 1.2 to 1.9 percent. Previous research demonstrates that a corn price increase is expected to influence retail egg prices to a lesser extent than farm egg prices (Babula and Bessler 1989a). Retail price includes more transportation, packaging, and marketing costs than farm prices, and poultry feed costs are a smaller component of the retail egg price (Babula and Bessler 1989a, p.20).

A price sensitivity parameter (PSP) may be calculated from the impulse responses and may be used to compare the relative degrees of response of the egg prices to corn price change. Recall that by a VAR model's definition, each of the three equations contains lags of all three modeled indices, such that the exogenously placed corn price increase sets all three VAR equations into motion. To calculate an egg price's PSP, the egg price's impulses are summed over the 17-month range of general significance, and are then divided by the corresponding corn price change. Since each impulse approximates a percentage change in the nonlogged index, the summation of impulses of a price index represents an accumulated percent change in the index over the chosen summation period. Such summations of egg price

⁵Pursuant to an anonymous reviewer's suggestion, an alternative ordering, PC/PR/PF, was run. Results from analyses of this additional run's impulse responses and FEV decompositions were substantially similar to results which emerged from our chosen ordering. Runs of the alternative ordering are available on request.

PERCENT CHANGE
IN PRICE INDICES



All impulse responses that are statistically non-zero at the one-percent significance level are denoted with solid characters.

Figure 1. Impulse Response in Egg Prices to a One-Time Increase in Corn Price

impulses are accumulated percent changes in the indices over the 17-month period when statistically non-zero change was observed. Each sensitivity parameter of egg price to corn price change represents a percent change divided by a percent change and resembles an elasticity defined for the period of the response variable's statistically significant change. For farm egg price, the sensitivity parameter of 0.40 suggests that each percent of corn price change is associated with slightly more than one-third of a percent of statistically significant change in the farm egg price.

For the retail egg price, the parameter value of 0.32 suggests that each percent of corn price change is associated with about one-third of a percent of statistically significant change in the retail egg price. The less-than-unity nature of these sensitivity parameters coincides with previous research in indicating that egg price responses are usually less than the corn price change, and that egg price responses to corn price change become weaker for pricing points located further down the marketing chain from the farmgate (Babula and Bessler 1989a, b).

Decompositions of Forecast Error Variance

Analysis of forecast error variance (FEV) is another tool of VAR econometrics for discerning relationships among the modeled system's time series. FEV is, at alternative forecast horizons or steps, attributed to shocks in each of the dynamic system's series, such that a measurement of relative "strength" of relationships emerges. Error decompositions attribute within-sample error variance to alternative series and thus give measures which are useful in applied work. Table 1 contains selected FEV decompositions for the three prices.

A variable's exogeneity is suggested when its FEV is largely attributed to its own variation. Likewise, a variable is highly endogenous to the system when small proportions of its FEV are attributed to its own variation, and large FEV proportions are attributed to the innovations of other variables (Bessler 1984a, b).

A number of results emerge from Table 1. ⁶ Corn price is largely exogenous with more than 93 percent of its FEV being self-attributed at all reported horizons. Farm egg price is exogenous, but to a more moderate degree than corn price. More than 62 percent of PF's uncertainty is self-attributed. More than

⁶Table 1 provides further evidence of the VAR model's stationarity. Stationarity is suggested because while each equation's standard errors in Table 1 continue to increase at the longer horizons, the standard errors do so by "leveling-off" toward particular values at the longer horizons (steps 35-36) (Bessler 1984a).

Table 1. Proportions of Forecast Error Variance k Months Ahead Allocated to Innovations of Corn, Farm Egg, and Retail Egg Prices

Response Variable	Steps k	Std. Error	Innovation Variable		
			PCN	PF	PR
----- percent -----					
Farmgate corn price:					
	1	.0777	99.44	0.10	0.46
	6	.1441	95.93	0.11	3.96
	12	.1879	95.56	0.12	4.31
	18	.2113	94.85	0.12	5.04
	24	.2257	94.67	0.36	4.97
	35	.2361	93.81	1.40	4.79
	36	.2364	93.74	1.44	4.82
Farm-level egg price:					
	1	.0936	5.94	93.57	0.49
	6	.1251	17.04	81.93	1.03
	12	.1374	25.68	72.89	1.43
	18	.1456	32.27	66.12	1.61
	24	.1508	31.58	66.37	2.05
	35	.1563	34.60	62.52	2.87
	36	.1569	34.92	62.17	2.91
Retail egg price:					
	1	.0608	9.82	67.41	22.77
	6	.0914	19.84	67.84	12.33
	12	.1030	28.77	61.26	9.97
	18	.1103	36.57	54.13	9.30
	24	.1142	35.28	54.48	10.23
	35	.1186	36.49	51.11	12.40
	36	.1191	36.62	50.79	12.58

30 percent of PF's FEV is, however, attributed to corn price at most reported horizons. Retail price contributes little to farm egg price's explanation.

Retail egg price is highly endogenous, with no more than 12.6 percent of its FEV attributed to own-variation at all reported horizons beyond one month. Farm egg price, the heaviest contributor, accounts for more than half of the retail price's FEV at all reported horizons. Corn price's uncertainty, the second most important contributor, accounts for more than 28 percent of PR's FEV at most reported horizons.

Declining volumes of egg production marketed at the farm pricing point and increasing production proportions being contracted have raised questions concerning the relevance of the farm pricing point for eggs (Lasley). Table 1's results suggest that despite the declining marketing shares associated

with farm egg price, PF is still an important (and perhaps widely-watched) informational variable. Farm egg price accounts for most of the retail price's variation—from 51 to in excess of 67 percent. Furthermore, the relationship appears unidirectional from farm to retail egg price, with minor proportions (less than 3 percent at all reported horizons) of PF's FEV attributed to retail price. Thus, despite the declining shares of egg production traded independently, evidence suggests that farm egg price continues to be an important and widely observed egg price indicator.

An interesting corn/egg price relationship emerges from analysis of the results of two different VAR econometric tools: (1) a combined application of the impulse response function and the Kloeck-Van Dijk Monte Carlo generator, and (2) the FEV decompositions. The sensitivity parameters for PF and PR impulses suggest that egg price response to corn price movements is less than one-for-one—that is, the parameters are below unity. More specifically, these parameters are 0.32 and 0.40, that is, within the vicinity of one-third. The FEV decomposition results (Table 1) suggest that corn price accounts for about one-third of egg price forecast error variances at most reported horizons. These results suggest that egg prices at the farm and retail levels respond (in the same direction) by roughly one-third of the percentage shock in farm corn price.

CONCLUSION

This study provides information about the dynamics of how the three modeled prices move between the pre-shock and post-shock equilibria modeled by more conventional and theoretically-based econometric models. A number of such policy-pertinent and dynamic results about the PCN-PF-PR price transmission emerge.

Farm and retail egg price responses have immediate reaction times to a rise in farmgate corn price. Egg price at the farm and retail levels increase in the wake of the positive corn price shock. Farm and retail egg price responses to the corn price shock persist for 17 months. That is, the historical dynamics embedded in the model would have corn price shocks being felt through the economy's egg-related sectors for about a year and a half. Change in corn price appears to elicit similar response patterns at the farm and retail sectors of the egg-related economy. Farmgate corn price appears highly exogenous in the modeled price transmission mechanism. Evidence suggests a high degree of farm egg price exogeneity. Retail egg price is endogenous, and appears highly influenced by the farm egg price. Further, farm egg price appears to in-

fluence retail egg price to a far greater degree than retail egg price influences farm egg price. Despite the declining egg volumes traded at the farm pricing point, evidence suggests that farm egg price is still

an important egg price indicator. Finally, evidence suggests that egg prices respond by roughly one-third of the percentage change in corn price.

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