MEASURING LEADS AND LAGS AMONG PRICES: TURKEY PRODUCTS

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The study applies the Haugh procedure for establishing Granger causal orderings among prices for whole turkeys and turkey parts Breast prices and a yield-weighted index of parts prices led tom prices by 1 day The reduction in uncertainty about tom prices in one period gained from knowledge of breast prices in the prior period is of little economic significance Results for canner prices relative to parts prices are similar

Keywords

Causality
Leads and lags
Dynamic regression
Pricing
Price reporting

INTRODUCTION

Marketing economists, government, and market participants are paying increasing attention to commodity pricing system performance (*10*) [1] The pricing system for turkeys has characteristics which have created problems in other commodity pricing systems Coordination of production and processing through contracting and integration has all but eliminated a spot market for live turkeys Proliferation of product variations, formula pricing, and fewer turkeys marketed as plain, whole, and frozen birds have led system participants to ask why live birds are still priced based on the quote for processed whole birds Price sensitivity and quality (whether due to reporting failure by market participants or reporters) have been questioned (*18*)

This article explores the lead-lag relationships between prices of a subset of over 100 turkey product prices reported in the *Producers' Price-Current* of Urner Barry Publications, the most widely used source of such information in the United States We include in the comparisons an index of turkey part prices weighted to show the part they represent of the whole turkey

We investigate the relationships between different product prices at different times (leads and lags) for two reasons First, given the large number of items quoted each day, one would expect reporters to vary the amount of attention they can give to each product price Thus, some prices may be more sensitive to changing conditions and lead others in time Second, the demand for whole turkeys for further processing (an alternative to sale as a fresh or frozen bird and a potential use for any turkey of sufficient size) stems from consumer demand for parts or further processed products One would expect that prices of some parts would lead those of whole birds, particularly the price of canner turkey (bulk-packed, fresh, without neck and giblets) which is destined for further processing Such price leading refers to only major parts (especially turkey breast) We do not expect minor parts such as the skin or tail to have strong leading tendencies

The methodology used in this article centers on the empirical specification of dynamic relationships between alternative variables (series) To date, most econometric research has involved estimating relationships specified *a priori* Typically, knowledge of these is based on economic theory or constraints peculiar to the system analyzed For example, countless empirical studies have been grounded in the theory of the firm or the consumer Generally this theory has provided justification for zero-one type restrictions in econometric equations (variable X belongs or does not belong in a particular equation) Economic theory has also been used to provide inexact prior information, for example, instead of including or excluding variable X in a relationship, the researcher posits that inexact restrictions make the coefficient associated with the variable positive (*17*) Often, however, *a priori* specification cannot be done because the analyst does not know the "correct" theory For example, in constructing dynamic models, theorists are not always explicit on the leads and lags which drive the system (*13*, p 227) Or, economists may have two, three, or more competing theories from which to choose—each yielding different policy recommendations for a given problem When a theory is ambiguous on explicit time-related properties, the method we use can be applied to help the analysts decide

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[1] Italicized numbers in parentheses refer to items in the references at the end of this article

on the theory to use [2] While the method we use here has been the focus of considerable debate (see *21*) over the last 5 years, it now represents (in the words of Feige and Pearce) "an essential element of the economist's tool kit" (*5*, p 532)

GRANGER CAUSALITY METHOD

The analysis applied here generally fits under the heading of Granger causality The method provides a means for establishing lead-lag (pre dictive) relationships among two variables reported in a time series More specifically, a variable X causes another variable Y, for a given universe that includes at least X and Y, if current values of Y can be predicted better by using past values of X than by not doing so, other things being equal The method has been used before, probably the most well known applications are (*19*) and (*14*) A recent article by Bishop in this journal provides a good review of the method (*2*)

In general, it is hard to detect causality by analyzing cross correlations or regressions of levels of Y on past levels of X and Y In particular, the significance tests (t and F statis tics) obtained from relating levels of highly autocorrelated series can be grossly overestimated, which could lead us to assert a causal relation when none exists Granger and Newbold, in an example of improper inference, demonstrate that high values of the coefficient of determination (R^2) can be obtained for regressions of one random walk on another (*7*) They conclude that unless caution is used with time series, essentially false regressions can be mistaken for genuine relationships

As an alternative, Haugh suggests that we consider the innovations of each series (*8*) That is, he suggests that we first remove all time series properties from each series—that we filter both series using procedures of, say, Box and Jenkins (*3*) The innovation of a particular time series refers to that part which cannot be explained in terms of its own past Innovation is used because it repre sents the new information available at time t for forecasting future periods (econometricians might prefer to use the term "error" to denote the same concept, which is perfectly acceptable)

The idea of filtering (or prefilter ing) data before attempting to make causal inference between series, while relatively new in economics literature, has been known to statisticians for some time Indeed, R A Fisher (in the first quarter of this century) suggested that one prefilter data with polynomial trend models (*6*)

Since Fisher's early writing on the subject, more general filtering procedures have been developed While possible filters are many, those used here fit into the class of autoregressive, integrated, moving-average (ARIMA) processes Some researchers may find it useful to view prefiltering as removing all time-related dependence, such as trends, cycles, or seasonal effects, from each series We chose the Box and Jenkins procedures because they offer a rich, well-developed, easily obtained set of procedures and computer programs Other methods are available (see *1* and *12*) An alternative procedure may provide a better path than ours to finding appropriate prefilters in specific cases [3]

Pierce and Haugh demonstrate that variable X causes Y if the cross correlations between the innovations from each transformed series are nonzero at positive lags—that is, if current Y can be predicted by past X

Other causal relations involving instantaneous causality, feedback, and independence can be analyzed by these same cross correlations For example, if the cross correlation is nonzero at a lag of zero, and no two way causality exists, instantaneous causality exists Or, if nonzero cross correlations exist at both positive and negative lags, then a two-way or feedback relation exists between X and Y

The actual test of these cross correlations must, of course, be carried out with estimated cross correlations Haugh has demonstrated that, under the null hypothesis that series X and Y are not causally related, r_k, the estimated cross correlations, are asymptotically independent and normally distributed with zero means and standard deviations of $1/\sqrt{n}$ Thus, we can test using Haugh's U statistic

[2] For more on the use of empirical methods to sort out "correct" theory, see A W Burks (*1*) He discusses the choice among completing theories of universal gravitation of Kepler and Newton While deduction—mathematics and *a priori* reasoning—was required to determine the truth of these competing theories, it was not sufficient

[3] Hsiao apparently feels this about Akaike's autoregressive "final prediction error" criterion (see *11*) In particular, Akaike's method takes some of the judgmental work out of time-series filtering

$$U_m = n \sum_{k=1}^{m} r_k^2 ,$$

where n refers to the number of observations on the innovations of X and Y, r_k^2 the squared cross correlations at lag k, and m is an integer, greater than or equal to one, chosen large enough to include expected nonzero coefficients Under the null hypothesis of series independence, the U statistic will be distributed χ^2 with m degrees of freedom For large empirical U values, we want to reject the hypothesis of series independence More explicitly, we can test for causality running in either direction (X causes Y (X → Y) or Y causes X(Y → X)) by cross correlating the innovations of X_t (call these u_t) and the innovations of Y_t (call these (v_t) Considering first correlations of u_t and v_{t+k} for $k = 1,2,\ \ \ , m$, we reject the hypothesis of series independence and thus infer causality from X to Y if U_m exceeds the tabular χ^2 (m) at a predetermined level of significance Conversely, considering the cross correlations of v_t and u_{t+k} for $k = 1,2,\ \ \ \ m$, can give us an analogous U_m statistic to test causality running from Y to X

Sims and Pierce and Haugh have pointed out problems associated with the application of the test statistic Most of these problems mean that we fail to reject the null hypothesis of series independence when we should reject it In particular, once we reject the hypothesis of series independence going one way, say from X to Y, the test statistic tends to underestimate the level of significance for causality running in the other direction, from Y to X (feedback) This problem is being researched, and currently no convenient alternative exists Pierce suggests that where one is seeking empirical evidence on how the world works this underestimation is not likely a serious limitation (*14*) The selection of the integer m is also bothersome, problems can arise from selecting it "too small" or "too large" Thus it is suggested that one give prior thought to selection of m, it should not be selected arbitrarily, but rather according to one's prior expectations on leads or lags (*14*)

APPLICATION OF HAUGH'S CAUSALITY METHOD

We now apply Haugh's two step procedure to the 1978 daily price quotes on seven of the turkey products and the turkey parts index We excluded the minor parts (trim and skin), skin price did not change during 1978 We will analyze only the influence of parts prices on whole birds prices and whole birds prices on parts prices, we exclude relationships among parts Weights used in construction of the price index are shown below [4]

Item	Index weight
Young toms, 20 22 pounds	not applicable
Canner packed, 20 pounds and up	not applicable
Boneless, skinless breast	0 260
White trim	011
Dark trim	012
Whole wing	117
Boneless, skinless thigh	135
Drum	130
Tail	018
Skin	080

[4] The weights represent the percentage of weight of tom turkeys attributed to each part The weights do not sum to one because turkey bone has no economic value

Following Haugh's approach, we filter each series separately to remove all time series properties which can be identified in each series To do so, we apply the three-step procedures of Box and Jenkins Readers interested in the autocorrelation and partial autocorrelation functions on each series can obtain these by writing to us We found that all time series properties in each series could be removed using an integrated moving average process of order 5 (this reflects a weekly regularity in price quotes)

$$(1\text{-}B)P_t = (1\text{-}\theta_1 B^1 - \theta_2 B^2 - \theta_3 B^3 - \theta_4 B^4 - \theta_5 B^5) e_t$$

Here P_t refers to the price of a particular turkey product in period t, B, the usual lag operator ($B^i P_t = P_{t-i}$), θ_i, a moving-average term to be estimated for each series, and e_t, the error or innovation in the process in period t We estimated a separate filter of this class for each turkey product To test the adequacy of this model, we applied Box and Pierce's Q statistic to the residuals estimated from use of this model over the fit period (usual procedure) The Q statistic resembles the U statistic described above While U is formed with squared cross correlations at lags $1,2,\ \ \ , m$, Q is formed with squared autocorrelations at lags $1,2,\ \ \ , m^*$ If we have prefiltered correctly, no autocorrelation should exist in the residuals (innovations) of each series Under the null hypotheses of independent residuals (of the same series), Q is distributed χ^2 with m^*-5 degrees of freedom The Q statistics appear in table 1

Table 1—Calculated Q statistic applied to residuals from filter to turkey price series

Price	Calculated Q[1]
Tom turkeys	15 12
Canner turkeys	8 39
Breast	13 50
Thigh	15 01
Wing	17 28
Drum	3 45
Tail	4 33
Index of parts	12 45

[1] χ^2 05 (14) is 23 7 In all cases the Q statistic is below this value Thus, we cannot statistically distinguish the residual from a random series

In all cases, the Q statistic falls well below the χ^2 value for 14 degrees of freedom To illustrate further the adequacy of the applied filter, we list the first 10 autocorrelations of observed residuals (table 2) The autocorrelations are all relatively low which suggests no serious departure from white noise (independent) residuals

Following Haugh's two-step procedure, we cross correlated the innovations (residuals) from each series at lags of 30 days in both directions Causality tests are summarized in table 3 Here we list the calculated U statistics for 24 bivariate comparisons among turkey price series We have calculated two U statistics for each comparison We give U_2 for short lags We decided that important leads and lags, if they exist, would be observed at short periods—one or two periods We calculated U_{10} to attempt to capture any longer lead lag relationship Our prior beliefs did

Table 2—Autocorrelations of residuals from the application of filter to each turkey price series[1]

Price series	1	2	3	4	5	6	7	8	9	10
Tom turkeys	-0 04	-0 04	-0 02	-0 05	-0 05	-0 09	-0 06	-0 00	-0 10	-0 07
Canner turkeys	- 01	- 01	- 02	- 01	- 00	11	02	- 07	11	03
Breast	- 00	- 00	03	03	02	07	01	13	04	01
Thigh	01	02	01	02	02	15	11	05	08	07
Wing	00	- 00	00	01	00	10	- 01	05	11	04
Drum	- 00	- 00	- 00	- 00	00	- 00	05	- 01	- 06	09
Tail	- 01	- 01	- 01	00	00	- 01	- 01	- 01	13	- 01
Index of parts	01	00	02	02	03	09	02	10	- 00	08

[1] Asymptotic standard errors are 0 07 at low lags

Table 3—Calculated U statistics for alternative causal orderings of turkey prices[1]

Turkey part	Tom turkeys		Turkeys for canning	
	As effect	As cause	As effect	As cause
Index				
U_2	[2]6 19	1 35	1 95	3 44
U_{10}	14 81	8 54	11 80	12 74
Breast				
U_2	[2]12 28	16	3 22	4 02
U_{10}	[3]18 33	7 08	15 68	18 02
Thigh				
U_2	84	1 68	66	5 05
U_{10}	10 37	6 97	8 81	9 53
Wing				
U_2	92	[2]6 33	44	1 00
U_{10}	7 26	13 77	7 78	8 84
Drum				
U_2	64	1 25	3 38	3 34
U_{10}	18 09	14 29	12 32	4 84
Tail				
U_2	68	[2]11 96	2 87	[2]28 12
U_{10}	3 56	[3]38 76	10 01	[3]61 53

[1] Only a small subset of all possible price comparisons appear here The focus is on parts prices that lead or lag whole turkey prices

U_2 is calculated from the first two cross correlations (lags 1 and 2) It is distributed χ^2 with two degrees of freedom The critical value for rejecting the hypothesis that the two cross correlations come from random series is 5 99 at the 5-percent level

U_{10} is calculated from the first 10 cross correlations (lags 1 through 10) It is distributed χ^2 with 10 degrees of freedom The critical value of rejecting the hypothesis that the 10 cross correlations come from random series is 18 30 at the 5-percent level

[2] Values are above the critical value of 5 99

[3] Values are above the critical value of 18 30

Our primary purpose here was to look for an individual part series which could be seen as a leading indicator of whole bird prices

not admit leads and lags encompassing more than 10 quotes [5]

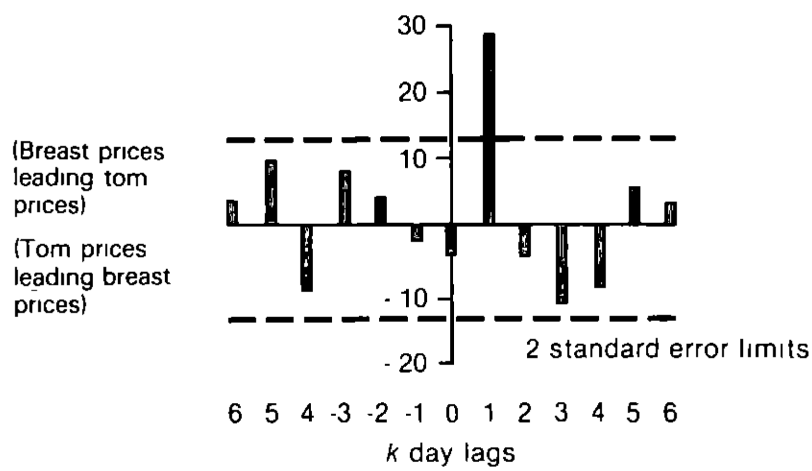
The results summarized in table 3 provide little evidence to suggest that whole bird prices lead the individual parts prices While tom prices do tend to lead whole wing and tail, they do not lead breast, thigh, drums, or the index of parts A similar argument holds for canner prices That is, while canner prices clearly lead tail prices, we observed no significant ordering for canner prices and the other parts prices

At least some of the turkey parts prices lead the whole bird prices A strong relationship is found between breast and tom prices—at both low and high lags Further, the index series leads toms at low lags No significant causal relationship runs from the prices of other bird parts to either toms or canner prices

Note from table 3 that, where evidence of causality is found, no reverse or feedback causality accompanies it That is, we observe, say, breast prices leading tom prices at low and high lags, but we do not observe a symmetric relation in which tom prices lead (feed back on) breast prices Thus, one can build a dynamic regression model that links the price series of toms to that of turkey breasts Such a model will in general improve our ability to forecast tom prices beyond that achieved by using only past tom prices If we observe feedback relations we cannot build a dynamic regression (*9*) We must rely on more general bivariate methods These are not considered here

To show the type of dynamic regression model which can be constructed, we consider the cross correlations between turkey breast and tom prices in greater detail (chart) Cross correlations between the innovations on breast prices and whole turkey prices are plotted at positive lags (breast leading toms) and negative lags (toms leading breast)

Cross Correlations Between Innovations on Breast and Tom Turkey Prices



Note $(1/\sqrt{n} = 0\ 07)$

[5] An anonymous referee suggested we also report the critical regions for the table as a whole While we did not originally want to make an overall test (we were looking for significant individual relations), under some conditions we think this overall test makes some sense That is, to require that the chance of making a type I error for the entire table be 0 05, we must use a 0 002 significance level on each individual relation The critical χ^2 values at a significance level of 0 002 for 2 and 10 degrees of freedom are 12 38 and 27 66, respectively While we do not test each individual relation against this overall significance level, we report it for completeness

Dotted lines in the figure represent the usual two standard error limits. Note that only the cross correlation at lag one exceeds this interval. Thus, we regressed the innovations on tom turkey prices in period t on the innovations of turkey breast prices in period t-1. Our results from this regression are

$$e_{T,t} = \underset{(2.65)}{0.05} + \underset{(3.57)}{0.10} e_{B,t-1},$$

$$d.w. = 2.03^{6}$$

While our degree of explanation is low ($R^2 = 0.06$), we observe a significant coefficient on the breast innovations variable. We can now substitute the expressions for $e_{T,t}$ and $e_{B,t-1}$ back into our univariate series representations of tom and breast prices. We can then forecast future values of the tom price series based on knowledge of past errors (innovations) in the breast representation.

The residual standard error from the univariate tom series was 0.272. This error was reduced to 0.257 or about 6 percent, with the additional knowledge of the previous innovations (errors) in the univariate breast series.

[6] Entries in parentheses are t statistics, associated with the null hypothesis that the coefficients are zero. The $e_{T,t}$ refers to innovation in tom prices and $e_{B,t}$ to innovation in breast prices. The Durbin Watson (d.w.) statistic is used to assess any first-order correlation pattern in the residuals of this regression. The calculated statistic does not lead us to suspect first-order autocorrelation in the residuals of this regression.

CONCLUSIONS

There seems to be no consistent lead-lag pattern from parts prices to whole bird prices or from whole bird to parts prices. Breast prices (tested individually) lead whole bird prices by 1 day. However, other parts—tail and possibly wing—seem to follow the whole bird prices. Of course, we did not test for parts leading other parts. One would have to make such a test to make a proper statement on relation among parts. Conceivably, the strong relation between prices of tails and toms results from the fact that both series follow breast prices but at different time lags.

Our primary purpose here was to look for an individual part series which could be seen as a leading indicator of whole bird prices. Breast prices based on table 3, should be considered as a candidate (at least for tom prices). However, further study, particularly the dynamic regression between the innovations of toms in t and the innovations of breast in t-1, suggests that little uncertainty is reduced due to prior knowledge of breast prices.

Some have questioned the accuracy or sensitivity of price quotations for whole, frozen, ready-to cook turkeys, which are usually used as a base for live bird pricing formulas. The number of reportable transactions involving the plain whole bird represented by the quote has been declining as more product is sold cut up, as further processed, or as a branded or otherwise differentiated whole turkey. Thus, we asked if a value index based on parts, or a subset of parts prices, is a better indicator of turkey value than the whole turkey quote.

We assume that, over a period of time, the whole bird quote will reflect market clearing (equilibrium) value. Likewise, the set of parts prices, weighted by yield of the parts, will, in time, reflect equilibrium value. Individual parts prices need not reflect whole bird values.

If one (or a specific set) price series can be shown to lead another related series, we consider it evidence that the leading series more accurately indicates changes in equilibrium value. This is particularly important for turkeys as formula prices at one stage are based on prices at another stage. If one price or set can be shown to lead another, that leading series is the better pricing base.

The yield weighted parts prices would be expected to indicate change in turkey value. But such an index does not lead or lag frozen, whole bird quotes significantly. Thus we find no reason to suggest use of a parts price index. Nor do we consider the reduction in residual error gained by using the breast prices to be operationally significant.

The methods applied in this study can be used to identify leads and lags in other price series. They could also help in efforts to compare the sensitivity or accuracy of price reporting or of the price discovery process.

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