Farmgate, Processor, and Consumer Price Transmissions in the Wheat Sector

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Abstract. *Time series techniques (vector autoregression or VAR) are employed to model a three-price dynamic system of the farmgate, processor, and consumer prices of wheat-related goods An increase (presumably drought-induced) in farmgate wheat price is simulated to determine impacts on processor and consumer prices in the wheat sector Several findings emerge First, the increase in farm wheat price (PF-increase) may be expected to immediately generate processor price increases which are statistically significant for almost a year Second, the PF-increase is expected to generate wheat-related consumer price increases, which are mostly significant for 22 months Consumer price increases of wheat-related goods are expected to peak in strength at about the 8-month point following the PF-increase And third, the consumer price increases are expected to be more gradual, less acute, but of longer duration than the processor price rises*

Keywords. *Vector autoregression (VAR), Kloek-Van Dijk t-values, drought, decompositions of forecast error variance, farmgate, processor or industrial, and consumer prices of wheat-based goods, farm/nonfarm price transmissions*

The year 1988 was one of serious drought for American agriculture The drought's grain supply shortfalls have bolstered grain prices (*14*, p 37)[1] By midsummer, prices of grain and grain-related products had already risen because of preharvest speculation and expectations (*9*) Looker (*9*) writes that, at that time, some had contended that "in nearly 20 years in the grocery business, [they] had never seen anything quite like the price increases announced Anything that's got grain seemed to be costing more as the drought scare pushed up commodity prices" Such statements indicate the casual observation and do not speak to the dynamics of price transmissions It is this dynamic process that farmers, food processors, consumers, and policymakers need to understand in order to make reasonable planning decisions when faced with a particular farm-level price shock An example of such a shock is the 1988 drought's rise in wheat price at the farmgate

We use time series techniques and construct a vector autoregression (VAR) model of a dynamic system of wheat-related farmgate, processor, and consumer prices Using this VAR model, we glean the empirical regularities from time-ordered data on these prices, gaining insight on the nature of the transmission mechanisms among these three wheat sector price levels We specifically trace through the impacts, on wheat-related processor and consumer prices, of a presumably drought-induced rise in farmgate wheat price Not specifically emphasized are the price effects of the 1988 drought, as done by Babula and Bessler (*1*) Rather, we demonstrate how one may use VAR econometrics and revealed empirical regularities about wheat-related prices to analyze how a "generic" farmgate increase in wheat price pulsates through the industrial and consumer sectors for wheat-based goods We presume the generic rise in wheat price to be drought induced

This study has several objectives We first estimate a VAR model of the wheat sector's system of farmgate, processor (or industrial), and consumer prices Second, we shock the VAR model with a rise in farm wheat price and analyze the impulse response patterns in processor and consumer prices of wheat-based products This analysis demonstrates how, and for how long, the presumably drought-induced rise in farmgate wheat price is expected to influence processor and consumer prices in the wheat sector The Kloek-Van Dijk procedure generated t-values for each impulse response to demonstrate how statistically significant (hereafter, significant) these impulses were (*7*) Third, we obtain and analyze decompositions in forecast error variance (FEV) for the model's three variables These analyses provide insight into the nature and the strength of the interrelationships among wheat related farm, processor, and consumer prices Such analyses uncover past data's empirical regularities and indicate how the time-ordered series have moved through time These past trends suggest how history would have wheat-related industrial and consumer prices respond to such a current farm sector price shock as the 1988 drought's increases in farm wheat price

VAR Econometrics

Under rather general conditions, an m-component vector, indexed by time period t, admits an autoregressive representation generally expressed as relation 1

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[1]Italicized numbers in parentheses cite sources listed in the References section at the end of this article

(*11*) (Note bold-faced characters represent matrices or vectors)

$$\mathbf{x}(t) = (\mathrm{SUM}(s = 1,\mathrm{inf}))[\mathbf{b}(s)*\mathbf{x}(t-s)] + \mathbf{e}(t) \tag{1}$$

Here, SUM(s = 1,inf) is the summation operator for variable "s" over the range of 1 0 through infinity (inf) The "s" denotes the lag order The **b**(s) are m*m matrices of autoregressive (AR) regression coefficients and **e**(t) is an m-element vector of white noise residuals (or innovations) The white noise nature of **e**(t) satisfies equations 2 and 3 (*2, 3, 4*)

$$E(\mathbf{e}(t)) = \mathbf{0} \text{ for all t, and} \tag{2}$$

$$E(\mathbf{e}(t)\mathbf{e}(s)') = \mathbf{0} \text{ if t does not equal s, } = \mathbf{S}, \text{ a positive definite, m*m covariance matrix, for } t = s, \tag{3}$$

where "E" signifies the best linear predictor For applied work, relation 1's infinite lag sequence must be truncated to a number small enough to be operational but large enough for the residuals to approximate white noise (*2*, p 112) A universally accepted method of VAR lag selection, however, does not exist One choice used with some success is the Tiao-Box likelihood ratio test Bessler (*3*) provides a discussion of the test's properties and suggests its use in applied problems (Lutkepohl (*10*) provides a comparative analysis of alternative lag selection procedures)

Compared with more conventional, structural econometric analyses, VAR analysis is a new approach which gleans empirical regularities from time ordered data In doing so, it refrains from imposing *a priori* (theoretical) restrictions on data interrelationships Rather, VAR models loosely utilize theory to suggest which variables constitute a dynamic system in equation 1 All variables in the system are initially considered endogenous, whereby each variable influences itself and all others in the system with lags One purpose for fitting such models is to view the dynamic system with as few *a priori* restrictions as possible, allowing those regularities present in the data to reveal themselves Bessler and Kling (*4*) provide a discussion of some of the properties and attributes of VAR econometric techniques

Further, the VAR econometric technique addresses issues that are either ignored or inadequately treated by more conventional and theoretically based models (*2*, p 111) These issues include lag lengths and measurements in the strength of relationships among economic variables These issues also include the reaction times, durations, overall patterns, and statistical significance of responses of a system's modeled variables to a shock in one of the system's member variables

Estimated VAR Model of Wheat Sector Price Transmissions

We demonstrate how a presumably drought-induced rise in farmgate wheat price influences the wheat sector's processor and consumer price levels We chose a three variable VAR of the farmgate wheat price (PF), processing price paid for wheat inputs (PP), and consumer prices of wheat-related goods (PC) Hereafter, these are referred to as the farmgate, processor, and consumer prices, respectively

We formulate the following VAR model of a dynamic system comprised of PF, PP, and PC

$$\begin{aligned}
PF_t = a_{f0} + a_{fT}*TRD &+ a_{f1}*PF_{t-1} + \quad + a_{f12}*PF_{t-12} && (4)\\
&+ a_{f13}*PP_{t-1} + \quad + a_{f24}*PP_{t-12} &&\\
&+ a_{f25}*PC_{t-1} + \quad + a_{f36}*PC_{t-12} + f_t &&\\
PP_t = a_{p0} + a_{pT}*TRD &+ a_{p1}*PF_{t-1} + \quad + a_{p12}*PF_{t-12} && (5)\\
&+ a_{p13}*PP_{t-1} + \quad + a_{p24}*PP_{t-12} &&\\
&+ a_{p25}*PC_{t-1} + \quad + a_{p36}*PC_{t-12} + p_t &&\\
PC_t = a_{c0} + a_{cT}*TRD &+ a_{c1}*PF_{t-1} + \quad + a_{c12}*PF_{t-12} && (6)\\
&+ a_{c13}*PP_{t-1} + \quad + a_{c24}*PP_{t-12} &&\\
&+ a_{c25}*PC_{t-1} + \quad + a_{c36}*PC_{t-12} + c_t &&
\end{aligned}$$

All a-coefficients are regression coefficients, the f, p, and c subscripts on the a-coefficients refer to the PF, PP, and PC variables, respectively TRD is a time trend and captures influences associated with time The a_{f0}, a_{c0}, and a_{p0} refer to the intercept terms on the PF, PC, and PP equations, respectively The f_t, p_t, and c_t are the innovations for the PF, PP, and PC equations, respectively All data are seasonally adjusted All analyzed data are in natural logarithms because it is likely (*a priori*) that the three variables exhibit cointegratedness (*6*)

Monthly Bureau of Labor Statistics (BLS) data serve as PF, PP, and PC proxies We estimate over the 1979 1-1986 12 period in order to exclude the effects of the 1988 drought Farmgate wheat prices or PF are proxied by the producer price index (PPI) for wheat in the farm products group of indexes The PPI for flour, in the processed foods and feeds index group, represents prices paid by processors of wheat-related inputs Consumer-level prices for wheat-related goods are represented by the consumer price index, all urban consumers, flour and prepared mixes Note that PC has, relative to PF and PP, a "diluted" wheat influence and is generally expected to respond to farmgate wheat price movements more sluggishly than processor prices (*13*)

All estimation and analysis was accomplished on Doan and Litterman's package, Regression Analysis of Time Series (RATS) (*5*) The Tiao-Box likelihood ratio test results (not reported here) suggest a 12-order lag (*8, 12*)

Influences of a Drought-Induced Farmgate Wheat Price Increase

The impulse response function simulates, over time, the effect of a once-only shock in one of the system's series on itself and on other series in the system. This is done by converting the VAR model into its moving average (MA) representation. The parameters of the MA representation are complex, nonlinear combinations of the AR regression coefficients. We chose to impose a one-standard-error shock in the farmgate wheat price on the system. This shock represents a 2.9-percent increase.

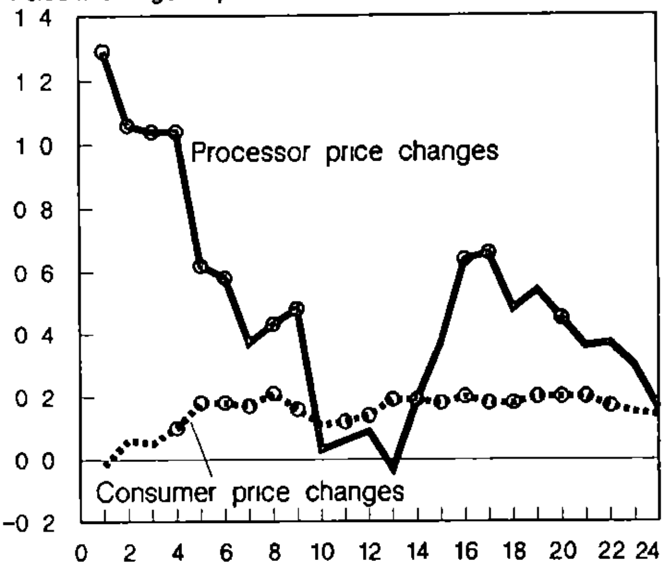
The PF, PP, and PC equations may have contemporaneously correlated innovations. Failure to correct for contemporaneously correlated current errors in the VAR relations will produce an impulse response function which is not representative of historical patterns. We implement a Choleski decomposition in order to orthogonalize the current innovation matrix, such that the variance/covariance matrix of the transformed current innovations is identity. The Choleski orthogonalization attempts to resolve the problem of contemporaneous feedback, which distorts impulse responses.

The Choleski decomposition requires a sometimes arbitrary imposition of a Wold causal ordering or chain among the current values of the dependent variables. We chose the ordering of PF to PP to PC for two reasons. First, intuition suggests that farm prices more directly affect processor prices than they affect consumer prices, and that processor prices more directly influence consumer prices than do farm prices (*1*, *13*). Second, we simulate the effects of a farm price increase, presumably drought induced, on processor and consumer prices of wheat-related goods. The question investigated, therefore, suggests the ordering.

The farmgate price shock will now refer, in this article, to the presumably drought-induced rise in farmgate wheat price or PF. Months or steps will refer to the number of months following the farmgate price shock. (Step 1 is when the PF increase occurs.) All prices are those of wheat-related products.

Figure 1 presents the impulse responses of processor and consumer prices to a one-standard-error rise (2.9 percent) in farmgate price. The impulse responses are changes in the natural logarithms of the PF and PC indexes and approximate percentage changes in the nonlogged indexes. We used Kloek and Van Dijk's (*7*) Monte Carlo procedure to generate t-values for each impulse response in wheat-related processor and

Figure 1
Impulse responses in processor and consumer prices of wheat-based goods from a rise in farmgate wheat price[1]



1/ Circled impulses are significantly different from zero at the 10-percent level.

consumer prices. One uses an impulse's t-value to decide whether the impulse is statistically significant (here at the 10-percent significance level). That is, one rejects the null hypothesis that an impulse response is zero and concludes that there is adequate sample evidence to accept the alternative hypothesis—that the impulse response is nonzero—when the absolute t-value exceeds the critical value at the chosen confidence level. All of figure 1's statistically significant impulse responses are circled. Most processor price (PP) responses are significant for the first year and insignificant thereafter. The consumer price responses which are less pronounced than the PP responses, are mostly significant for the first 22 months.

A number of results emerge from figure 1. Processor price immediately rises. These increases immediately peak at 1.3 percent, a change of less than half of the initiating 2.9-percent increase in farmgate wheat price. The processor price increases persist, but in a decelerating manner, for 12 months following the initiating PF increase before the impulses begin cycling downward through time in a path of diminishing strength. So, the processor price increases occur immediately following the farm price rise and may endure for approximately a year. Impulses in processor price take on statistical significance immediately, and most of these impulses are significant for the first year, after which most responses in processor price are not significant. We emphasize, therefore, only the first year of processor price responses.

A 3-month "reaction" time appears required for the farm-level shock in wheat price to be felt at the consumer level, because the consumer price impulses are not statistically significant until the fourth month Rather than peaking immediately, consumer price increases, as expected, gradually strengthen These increases peak in strength after about 8 months, and then extend out until almost the 2-year point, after which they become statistically insignificant Unlike the processing stage of wheat-related goods, a stage which is closely tied to the annual wheat production cycle, consumption and hence consumer prices of wheat related goods are not as annually oriented Figure 1 shows how the farm price increase significantly affects consumer price beyond the 12 months during which processor price effects are significant The consumer price rises are more gradually felt and more enduring than increases in processor price At their 8-month peak of 0 21 percent, the consumer price increases are less than the 1 3-percent peak rise in processor price and less than 10 percent of the initiating rise in farmgate price

The less pronounced, more gradual, but longer lasting nature of the wheat sector's consumer price impulses, relative to those of the processor price, may have a number of explanations These explanations have been provided in a similar analysis of wheat related prices (*1*) and are supported by this study's results (fig 1) First, wheat-based products' storability at the consumer level may account for consumer price impulses having reached peak strength in a more gradual manner than processor price impulses Wheat is storable, and consumer prices may take longer to respond fully because of the immediate inventory of wheat-related consumer goods made up of a previous and less costly crop Time is required before the warehouse and retail shelf supplies of wheat-based goods made with the previous crop are consumed, insofar as the consumer price impulses require 3 months before achieving statistical significance (*1*)

Second, the farmgate wheat price is more removed from the consumer price than the processor price in the food and fiber chain, and this may also account for the impulses being more gradual and less pronounced at the consumer level than at the industrial level Our results provide support for this explanation, insofar as the processor price impulses are larger than consumer price responses and take on statistical significance more immediately than consumer price impulses

Third, the influences of a farmgate increase in wheat price may be more moderate at the consumer stage than at the processor stage because farmgate price comprises a lesser proportion, that is, it has a smaller influence on the consumer price than on the processor price Processing and other additional services are added to wheat between the processor and consumer stages, and these nonwheat services may dilute the wheat price's influence on consumer price (*13*) (For example, there are the sweeteners, flavorings, and the packaging added to wheat-based food mixes)

And fourth, the consumer price increases may last longer at a statistically significant level than processor price increases because consumption of wheat-based goods is not as closely tied to the annual nature of wheat production as industrial price Consumption of wheat-based goods occurs throughout the year and may not be as closely tied to a 12-month production cycle as processor price Consumer price impulses may therefore last with significance beyond the year or so that processor impulses last

Decompositions of Forecast Error Variance

Analysis of decompositions of forecast error variance (FEV) is another tool of VAR econometrics for discerning the 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 a measure useful in applied work " (*2*, p 117) Decompositions of FEV are in table 1 We calculated FEV decompositions for 35 months or steps

With a stationary series, the standard errors increase out into time but level off toward a value (*2*) Table 1 suggests that PF, PP, and PC are stationary

A variable's exogeneity is suggested when its FEV is largely attributed to its own variation Likewise, a variable's endogeneity is suggested when small proportions of its FEV are attributed to its own variation, and when large proportions of its FEV are attributed to the other time series in the system

FEV decompositions suggest that farmgate wheat price is highly exogenous to the system At the reported horizons, no less than about 58 percent of PF's FEV is self-attributed Processor and consumer prices influence farm price FEV to a rather modest, but increasing, extent over time By the 35th month, PF's FEV is 22 36 percent attributed to processor price innovation and 19 69 percent attributed to consumer price innovation

Table 1—Proportions of forecast error variance, k months ahead, allocated to innovations in various price levels of wheat-based goods

Variable name	k	Standard error	Percentage explanation from PF	PP	PC
Farmgate price (PF)	1	0 0351	96 99	0 90	2 11
	6	0463	87 72	8 50	3 78
	12	0520	72 30	19 89	7 82
	18	0596	68 67	16 76	14 57
	24	0641	63 90	19 04	17 06
	34	0702	57 98	22 42	19 61
	35	0706	57 95	22 36	19 69
Processor price (PP)	1	0193	76 26	23 07	67
	6	0285	71 92	26 96	1 12
	12	0300	69 92	27 32	2 75
	18	0337	69 00	22 56	8 44
	24	0356	66 18	23 02	10 80
	34	0387	59 12	26 35	14 52
	35	0389	59 00	26 34	14 66
Consumer price (PC)	1	0041	2 40	1 00	96 60
	6	0072	21 41	29 83	48 76
	12	0094	29 66	37 06	33 28
	18	0107	41 50	31 98	26 52
	24	0118	46 24	28 27	25 49
	34	0134	42 05	28 84	29 11
	35	0136	41 60	29 15	29 25

Processor price's FEV decompositions suggest a high degree of PP endogeneity About 59-76 percent of processor price FEV is attributed to farmgate wheat price Minor portions of PP's FEV are attributed to own-variation and to consumer price error

Table 1 suggests a high level of endogeneity for consumer price Less than a third of PC's FEV is self-attributed at horizons beyond 6 months Farm price variation contributes most towards the explanation of the consumer price's FEV

Findings and Conclusions

An increase in farmgate wheat price may be expected to immediately generate statistically significant increases in wheat sector processor prices, and these increases may last for about a year Most of the industrial price rises are significant during this first year and insignificant thereafter A 3-month reaction time appears required before wheat-related consumer price responds to wheat price increases at the farm level The farmgate shock in wheat prices generates gradually strengthening consumer price increases that peak about 8 months after the farmgate shock The consumer price increases last, with most being significant, for 22 months following the drought-induced farmgate price increase The consumer price responses are more gradual, more tempered, but more enduring, than processor price impulses Insignificant until the fourth month, the consumer price responses are mostly significant through month 22

Farmgate wheat price is highly exogenous Processor and consumer prices are highly endogenous, and their FEV's appear mostly explained by farm price of wheat

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