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Dynamic U.S. Food-Related Inflation Relationships: A Cointegrated VAR Model Analysis

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Since the mid-1990s there has been little agricultural economics research on how macroeconomic shocks filter through to farm and food prices, with Awokuse's (2005) recent insightful article on the subject being an exception. Yet interest in the nature of such transmission mechanisms has noticeably increased in the wake of myriad recent global/U.S. macroeconomic and commodity events. The U.S. and global economies have plunged into deep recession since 2007, and in response the Federal Reserve and the Bush and Obama administrations have, since late 2008, implemented a number of economic stimulus measures that some deem as potentially inflationary. There also has been noted a post-2007 rise in the acceleration rate of U.S. and global food prices. The Congressional Research Service noted a marked acceleration in average annual U.S. food price increases to 4.0–4.5 percent since 2007—an acceleration rate that far exceeds the longer-run post-1987 average annual rate of 2.7 percent (Capehart and Richardson 2008, pp. 2–3).

We therefore propose a monthly cointegrated vector autoregression (VAR) model of the following five U.S. variables: the producer price index, or PPI, for all items (PPIALL), the PPI for crude petroleum (PCRUDE), the PPI for agricultural chemicals (PAGCHEMS), the PPI for farm products (PFARM), and the PPI for processed foods (PPROC). All five producer price indices are obtained from the Bureau of Labor Statistics of the U.S. Department of Labor (BLS/Labor 2008).¹ In

¹ All five U.S. producer price indices are monthly and are not seasonally adjusted. PPIALL is the PPI for all commodities. PCRUDE is the PPI for crude petroleum, series no. WPU0561. PAGCHEMS is the PPI for agricultural chemicals and chemical products, series no. WPU0561. PFARM is the PPI for farm products, series number WPU01. PPROC is the PPI for processed foods and feeds, series no. WPU02.

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so doing we hope to achieve two goals. First, we address the need for updated and policy-relevant research on how macro shocks dynamically influence food-related prices through two crucial farm-input price linkages (PAGCHEMS, PCRUDE) through analysis of cointegrating parameters and adjustment-speed coefficient estimates that emerge from the long-run error correction space. Second, we introduce a number of cointegrated VAR econometric method advancements/refinements that are not yet well known in the agricultural economics literature and that have been developed recently by numerous studies summarized by Juselius (2006). Such advancements/refinements include a comprehensive discernment of the modeled time series stationarity properties and consequential specification implications that achieve a statistically adequate model, expanded methods of discerning reduced rank of the cointegration space, and a new systems-based multivariate test of stationarity.

The Statistical Model: The Unrestricted Levels VAR and its VEC Equivalent²

Following Juselius (2006) we begin with a VAR model that posits each endogenous variable as a function of k lags of itself and of each of the remaining endogenous variables (Sims 1980). Tiao and Box's (1978) likelihood ratio lag-search method, corrected for small samples, was applied; results suggested a four-lag structure. Deterministic and trend components are added as the analysis unfolds. The levels VAR above may be re-written as the unrestricted vector error correction or VEC model:

$$(1) \Delta x(t) = \Gamma(1) * \Delta x(t-1) + \dots + \Gamma(k-1) * \Delta x(t-k+1) + \Pi * x(t-1) + \Phi * D(t) + \varepsilon(t),$$

where $\varepsilon(t)$ are residuals distributed as white noise, and with $k = 4$ lags; $x(t)$ and $x(t-k)$ are $p \times 1$ vectors of the five endogenous variables in current and lagged levels; $\Gamma(1) \dots \Gamma(k-1)$ are $p \times p$ matrices

² This section draws heavily on the work of Johansen and Juselius (1992) and Juselius (2006, pp. 59–66).

of short-run regression coefficients on the lagged differences; and Π is a $p \times p$ error correction term to account for endogenous variable levels. $\Phi \cdot D(t)$ is a set of deterministic variables: 11 centered seasonal and a host of other trend and dummy variables which will be added to address the data issues identified above as the analysis unfolds.

As shown later using Juselius' systems-based unit root test, the five endogenous variables are non-stationary, or $I(1)$, and the differences are thereby stationary, or $I(0)$. Differencing the nonstationary data to impose stationarity can elicit problems with mis-specification bias from omitted relevant information should the individually nonstationary variables be cointegrated and move in tandem over time. Equation 2 holds under "cointegration," a condition that occurs when the nonstationarities in one subset of the series cancel out those in another such that the system of individually nonstationary series behaves in a stationary manner as a group. This happens when Π , a $p \times r$ matrix, is less than full rank (p) and contains $r < p$ linear combinations of the individually nonstationary series called cointegrating relations or CVs. Π , known as the long-run error correction term, is decomposed as

$$(2) \Pi = \alpha \cdot \beta'$$

where α is a $p \times r$ matrix of adjustment speed coefficients and β is a $p \times r$ VEC coefficients.

The Γ -terms and Φ -term collectively comprise the short-run/deterministic model component.

Granger and Newbold (1986) note that potential adverse econometric consequences of failing to utilize information inherent in the modeled endogenous data's non-stationarity elements include compromised inference and spurious regressions. Juselius (2006, chs. 1–4) outlines a procedure with which to capture such nonstationary elements into a well-fitting unrestricted levels VAR and VEC equivalent before exploiting the system for cointegration.

Data analysis suggested inclusion of a linear trend (TREND) and various permanent shift dummies (presented below). A set of 11 centered seasonal were considered for Equation 2's short-run/deterministic component. Analysis led to consideration, where relevant, of outlier binary variables in the short-run/deterministic model component. Following Babula, Rogowsky, and

Romain (2006), we initially included the following permanent shift binaries in levels form in the long run component and in differenced form in the short-run/deterministic model components.

IRAQ1: valued at unity during August 1990–March 1991, and zero otherwise. This binary attempts to capture the influences of the first U.S. military action in Iraq on crude and crude-based prices.

CROSPK1: valued at unity from May 1995 through August 1996, and zero otherwise. This binary attempts to capture the influences of higher U.S. crop production levels from a period of extraordinarily favorable weather in the U.S. Midwest.

CROSPK2: valued at unity from April 2003 through July 2004, and zero otherwise. This binary was designed to capture the effects of unusually high world prices and demand levels for grains and oilseeds.

HIPCRU: valued at unity during April 2006–May 2008, and zero otherwise. Following Juselius' (2006, chs. 1–3) recommended data analysis of plotted data, this binary arose to account for the first of three recent escalations in world crude oil prices.

DPOIL0703ON: valued at unity from March 2007 through May 2008, and zero otherwise. Following Juselius' (2006, chs. 1–3) recommended data analysis procedures, this binary arose to account for the second of three recent periods of increases in world crude oil prices.

DPOIL07: valued at unity from September 2007 through May 2008, and zero otherwise. Following Juselius' (2006, chs. 1–3) for data analysis, this binary was defined to capture the third and most recent—and markedly more pronounced—escalation in world crude oil prices.

FAIRACT: valued at unity during September 1997–August 2002, and zero otherwise, to capture the effects on modelled variables of the implementation of the 1996 U.S. Farm Bill (FAIR Act).

NEWFBILL: valued at unity during September 2002–September 2004, and zero otherwise. This binary attempts to capture the effects of the implementation of the 2002 U.S. Farm Bill.

A variable was added and retained if Juselius' (2006) recommended diagnostic test values (discussed in Table 1) moved favourably and suggested

Table 1. Diagnostic Test Results for the Unrestricted VEC: Before and After Specification Efforts.

Test and/or equation	Null hypothesis and/or test explanation	Before specif. effort	After specif. efforts
Trace correlation	System-wide goodness of fit: large proportion desirable.	0.27	0.57
LM test for autocorrelation	Ho: No autocorrelation at 1 st lag.	36.0 (p = 0.07)	33.7 (p = 0.16)
Doornik-Hansen normality tests	Ho: Equation residuals are normal. Reject for values above 9.2.		
Δ PPIALL		102.6	8.6
Δ PCRUE		48.6	1.36
Δ PAGCHEMS		37.5	5.9
Δ PFARM		11.5	2.1
Δ PPROC		6.2	1.9
Skewness/& (kurtosis)	Skewness: Ideal is zero; small values desirable. Kurtosis: Ideal is 3.0; acceptable value range, 3.0–5.0.		
Δ PPIALL		-0.56 (6.4)	-0.01(3.9)
Δ PCRUE		-0.58 (5.6)	0.04 (3.3)
Δ PAGCHEMS		0.79 (6.4)	0.06 (3.7)
Δ PFARM		-0.18 (4.1)	-0.01 (3.3)
Δ PPROC		0.41 (3.5)	0.16 (3.3)

improved specification. All eight permanent shift binaries, a trend variable, and a set of 11 centered seasonal variables enhanced the battery of diagnostic values, so all were included.

We then began a set of further estimations, using the latter estimation as a base. Each time a potential outlier was deemed potentially of extraordinary influence based on a “large” standardized residual,³

³ We followed Juselius’ (2006, ch. 6) procedure for the analysis of potentially extraordinary effects of observation-specific events using “outlier” binary variables based on the Bonferoni criteria: $INVNORMAL[(1.0-0.025)^{(1/T)}]$, where $INVNORMAL$ is the RATS instruction for the inverse of the normal distribution function that returns the variable for the density function of a standard normal distribution (Estima 2007). The absolute Bonferoni value here equals 3.7 with a sample size of $T = 216$. We chose a conservative criterion: an observation was considered as a potential outlier if the absolute standardized residual value was from 3.0 to 3.7 or more. For

an appropriately specified binary variable was included in Equation 2’s short-run/deterministic component and ultimately retained if the battery of diagnostic values suggested improved specification. Ten such outlier binary variables were included.⁴

such observations, we placed an observation-specific transitory binary into the model’s short-run/deterministic component, and followed the above-noted process of sequential estimation and diagnostic monitoring. See Babula, Rogowsky, and Romain (2006, p. 43).

⁴ To conserve space, we have not included the extensive variable-by-variable analysis from numerous estimations that resulted in the inclusion of ten outlier binaries. All included variables are of the transitory “blip” construction described in Juselius (2006, ch. 6). A binary $dt0110_0111$ was designed to capture the transitory impacts of a drop in the U.S. wholesale price index during 2001:10, likely elicited by the start of the post-9/11 economic slowdown. In differenced form the variable was defined as unity for 2001:10, as -1.0 for 2001:

An adequately specified model should generate statistically normal residuals. Table 1 provides the battery of Juselius' (2006) recommended diagnostic test values for two estimations: the initially estimated unrestricted model before sequential estimations aimed at improved specification with no deterministic variables (other than a constant), and for the unrestricted VEC judged as adequately specified specification efforts. Table 1's results reveal clear improvement in model specification and benefits from focusing intense scrutiny on the modeled data's properties that Juselius contends are often inadequately considered. After such specification efforts the trace correlation (a goodness of fit indicator) approximately tripled, Doornik-Hansen values suggest notable progress

11, and zero otherwise. A binary $dt0010_0107$ was defined to account for the transitory positive pressures on crude oil price during 2000:11–2001:06. In differenced form the binary was defined as unity for 2000:11, as -1.0 for 2001:07, and as zero otherwise. A binary $dt0101_0106$ was defined to account for the upward transitory pressures on PAGCHEMS during 2001:01–2001:05 due to the concurrently rising prices of PCRUDE. In differenced form the binary was defined as unity for 2001:01, -1.0 for 2001:06, and zero otherwise. A binary $dt0204_0205$ was designed to capture transitory negative effects on PFARM during 2002:04. These effects were likely anticipatory impacts on U.S. farm product prices from the then-imminent passage of the 2002 U.S. farm bill. In differenced form, this binary is defined as unity for 2002:04, as -1.0 for 2002:05, and as zero otherwise. A binary $dt0511_0512$ was defined to capture the transitory impacts of a sharp 2005:11 drop in PCRUDE. This binary is defined in differenced form as unity for 2005:11, as -1.0 for 2005:12, and as zero otherwise. A binary $dt0509_0511$ was designed to capture the transitory effects of an upward movement in PPIALL during 2005:09–2005:10. This binary is defined in differenced form as unity for 2005:09, as -1.0 for 2005:11, and as zero otherwise. A binary $dt9010_9011$ was designed to account for extraordinary effects of the 1990:10 PCRUDE peak at 118. Such effects were likely over and above the effects that were captured by the above-defined permanent shift binary of IRAQ1 (and its associated short run differenced binary). The $dt9010_9011$ is defined in differenced form as unity for 1990:10, as -1.0 for 1990:11, and as zero otherwise. A binary $dt0303_0304$ was designed to account for the transitory effects from a shift upward in PAGCHEMS during 2003:03. This binary is defined in differenced form as unity for 2003:03, as -1.0 for 2003:04, and as zero otherwise. A binary $dt9311_9312$ was defined to account for the transitory effects from a 1993:11 upward shift in PAGCHEMS. The binary is defined in differenced form as unity for 1993:11, as -1.0 for 1993:12, and as zero otherwise. A binary $dt0609_0611$ was designed to capture the transitory impacts of an easing in wholesale price increases during 2006:09–2006:10. This binary is defined in differenced form as unity for 2006:09, as -1.0 for 2006:11, and as zero otherwise.

in the once highly non-normal residual behavior in achieving normality, and skewness/kurtosis values were ultimately within acceptable ranges. We conclude that the battery of diagnostic results reflect high levels of benefit to model adequacy by having followed Juselius' (2006, chapters 4–6) specification-enhancing efforts.

Cointegration: Choosing and Imposing Reduced Rank on the Error Correction Space

The five endogenous variables are shown below to be $I(1)$, and their differences are $I(0)$. The Π matrix in Equation 3 is a 5×5 matrix equal to the product of two $p \times r$ matrices: β of error correction coefficient estimates that under cointegration combine into $r < p$ stationary CVs of the five individually nonstationary endogenous variables, and α of adjustment-speed coefficient estimates (beta and alpha estimates, respectively). The rank of $\beta'x(t)$ is reduced despite $x(t)$'s five series being nonstationary.

A recent refinement in methods of the cointegrated VAR model is to extend the evidence considered in determining reduced rank beyond a traditional sole reliance on trade test results (Juselius 2006, p. 139) to include analysis of the patterns of characteristic roots in the companion matrix and examination of plotted CVs as well. Table 2 provides nested trace test evidence for rank determination. Taken alone, this trace evidence suggests that rank is 3.

As noted by Juselius (2006, pp. 141–142), if $r = 3$ is assumed, then there should be $p - r = 2$ restricted unit roots. Should the third root have been nonstationary and erroneously included in the model, the largest unrestricted root (here, the third) would approach unity, and the rank should be reduced (Juselius 2006, pp. 142–143). Under an assumed rank of three, the first three characteristic roots in the companion matrix are 1.0, 1.0, and 0.93. With the third root approaching unity, $r = 3$ should be reduced to $r = 2$.

Juselius (2006, pp. 142–143) contends that when a CV's plotted values exhibit stationary behavior, the CV should be considered as part of the cointegration space and not excluded. Plots of the three cointegrating relations (not included here due to space considerations) suggested stationary behaviour for the first two CVs, and clearly nonstationary behaviour for the third CV, suggesting a

Table 2. Trace Test Statistics and Related Information for Nested Tests for Rank Determination.

Null hypothesis	Trace value	95% fractile (critical value)	Result
Rank, r , is zero	227.7	103.0	Reject the null that r is zero.
Rank is 1 or less	149.9	80.1	Reject the null that r is one or less.
Rank is 2 or less	79.9	57.2	Reject the null that r is 2 or less.
Rank is 3 or less	36.8	40.1	Fail to reject the null that r is 3 or less.
Rank is 4 or less	10.0	26.9	Fail to reject the null that r is 4 or less.

CATS2-generated fractiles are increased by $8 \times 1.8 = 14.4$ to account for the eight binaries restricted to the cointegration space.

rank of two. We conclude that on balance the three sets of evidence suggest that the first two CVs, rather than the first three, should be considered within the error-correction space, and that Π 's reduced rank is 2.

Two cointegrating relationships emerged from using Johansen and Juselius' (1990, 1992) reduced-rank estimator. Not reported here due to space considerations, these CVs are not yet restricted for evidentially supported economic restrictions which emerge from the ensuing section's hypothesis tests (hereafter, the two unrestricted CVs). We normalized CV1 on PFARM and CV2 on PPROC.

Hypothesis Tests and Inference on the Economic Content of the CVs

We begin with the two unrestricted CVs, and conduct a series of hypothesis tests on $\Pi = \alpha\beta'$, impose the statistically supported restrictions, and then re-estimate the system with the reduced-rank estimator summarized in Johansen and Juselius (1990, 1992) and programmed by Dennis (2006). Hypothesis tests on the beta coefficients take the form

$$(3) \beta = H \cdot \varphi,$$

where β is a $p1 \times r = 2$ vector of β -coefficients on the variables in the cointegration space; H is a $p1 \times s$ design matrix, with s being the number of

unrestricted or free beta coefficients; and φ is an $s \times r = 2$ matrix of the unrestricted beta coefficients. Johansen and Juselius' (1990, 1992) well-known hypothesis test value is provided as

$$(4) -2\ln(Q) = T \cdot \sum [(1-\lambda_i^*) / (1-\lambda_i)] \text{ for } I = 1, 2 (= r).$$

The asterisked (non-asterisked) eigenvalues ($\lambda_i, I = 1, 2$) are generated by the model estimated with (without) the tested restriction(s) imposed.

Hypothesis Tests on the Beta Estimates.

We perform three sets of tests on the β -estimates: five stationarity tests for the endogenous variables, 14 exclusion tests,⁵ and a set of hypothesis tests on single β -estimates.

Tests of Stationarity

Following Juselius (2006, p. 297), this test for stationarity utilizes equation 3 rewritten as

$$(5) \beta^c = [b, \varphi].$$

For each of the five tests of stationarity on each endogenous variable, β^c is the $p1 \times r$ (here, 14×2) beta matrix with one of the tested endogenous variables (Juselius 2006, p. 183). The b vector is

⁵ The 14 variables are the five endogenous variables, the eight permanent shift binary variables, and a trend.

a $p1 \times 1$ (here, 14×1) vector with the following values: a unity value corresponding to the variable being tested for stationarity, zeros for the other four non-tested endogenous variables, and unity for the three deterministic components restricted to the correction space. Evidence was sufficient to reject the five null hypotheses that each of the endogenous variables is stationary.⁶

Tests of Beta Exclusions

Exclusion tests examine the null hypothesis that each of the 14 variables in the cointegration space have zero-valued β -coefficients in the two CVs. Failure to reject the null suggests that the variable should be excluded from the cointegration space.⁷ Evidence rejected the null hypothesis of zero-valued betas for all variables except for IRAQ1, CROPSPK2, NEWFBILL, and DPOIL0703ON, for which zero exclusion restrictions were imposed on the cointegration space.⁸

⁶ With nine deterministic components in the cointegration space and the imposed rank of $r = 2$, then Equation 5's test value is distributed under the null hypothesis of stationarity as a chi-squared variable with 11 degrees of freedom. Test values with parenthetical p-values are as follows, with the null of stationarity rejected for p-values less than 0.05: 68.7 (0.000) for PPIALL, 64.9 (0.000) for PCRUDE, 64.3 (0.000) for PAGCHEMS, 56.1 (0.000) for PFARM, and 68.2 (0.000) for PPROC.

⁷ Equation 3 includes a 14×2 β -matrix; a 14×13 design matrix, H , with 13 being the number of unrestricted beta coefficients in each relation; and a 13×2 matrix, ϕ , of 13 unrestricted coefficients in each of the three cointegrating relationships (Juselius 2006, pp. 266–268). Basically, the ϕ matrix is the β -matrix without the beta coefficients for the variable being tested for exclusion.

⁸ The exclusion test values (and parenthetical p-values) for the 14 variables were as follows with the null of zero-valued betas accepted for p-values above 0.05: 3.6 (0.17) for PPIALL; 11.8 (0.003) for PCRUDE; 6.5 (0.04) for PAGCHEMS; 24.9 (0.000) for PFARM; 22.1 (0.000) for PPROC; 1.9 (0.39) for IRAQ1; 18.8 (0.000) for HPCRUC; 24.1 (0.000) for CROPSPK1; 3.2 (0.20) for CROPSPK2; 7.0 (0.03) for FAIRACT; 2.4 (0.30) for NEWFBILL; 10.5 (0.005) for DPOIL0703ON; 1.7 (0.43) for DPOIL07; and 24.0 (0.000) for TREND. Evidence clearly accepts the null of zero-valued betas for DPOIL0703ON, NEWFBILL, CROPSPK2, and IRAQ1. Evidence seems to also accept the null of exclusion for PPIALL, for reasons which we cannot discern. However, we do not impose exclusion restrictions on the PPIALL betas, because of previous research that clearly suggests that PPIALL is an integral part of this system (Babula and Somwaru 1990).

Sequential Hypothesis Tests on Individual Beta Coefficients.⁹

Once we imposed reduced rank on Π and the four exclusion restrictions, two CVs emerged (not shown) that still must achieve the rank condition of identification. Meeting the latter condition requires choosing additional tests based on market expertise and economic/statistical theory, and then re-estimating the cointegration space with the reduced-rank estimator. One seeks out, tests, and follows other testable hypotheses with this procedure as well until two fully restricted CVs emerge with an array of restrictions that is accepted by the data.

Two zero-restrictions, one in each CV, were imposed to meet the rank condition of identification. Babula and Somwaru (1992, p. 249) suggested that there is a strong indirect link between crude oil price and farm prices through productive input prices, in order to rationalize an identifying zero restriction on PCRUDE's beta estimate in the first CV normalized on PFARM. We also chose to place the restriction of $\beta(\text{PAGCHEMS}) = 0$ on CV2 normalized on PPROC, insofar as agricultural chemical prices are more likely to influence processed food prices indirectly through input and farm prices. Summarized as Test Set 1 in Table 3, the first set of CV restrictions tested include the four exclusion restrictions in each CV, as well as $\beta(\text{PCRUDE}) = 0$ in CV1 and $\beta(\text{PAGCHEM}) = 0$ in CV2. Evidence from the chi-square test value of 7.9 and its p-value of 0.44 suggests strong statistical support for the acceptance of Test Set 1's exclusion and identifying restrictions. We repeated this process twice, and the tested and imposed statistically-supported restrictions are reported as Test Sets 2 and 3 in Table 3.

Discussion of the U.S. Transmission of Macro Influences on U.S. Food-Related Prices

The identified CVs fully restricted with Table 3's statistically supported restrictions are reflected by equation's 5 and 6, with parenthetical "t-values" reflecting the strong statistical strength achieved by the equations (as noted by Juselius, the t-values are not student t values and the critical values are ± 2.6 at the five percent significance level.)

⁹ This subsection is taken primarily from Juselius (2006, pp. 187–191).

Table 3. Sets of Sequential Hypothesis Tests on Specific Estimate Subsets.

Tested restrictions, restriction numbers in each CV	Explanation/reasons	Test value, parenthetical p-values, test results, and analysis.
Test Set 1: Exclusion and indentifying restrictions.		
<p><u>5 in CV1:</u> $\beta(\text{IRAQ1}) = \beta(\text{CROPSPK2}) = \beta(\text{DPOIL07030N}) = \beta(\text{NEWFBILL}) = 0; \beta(\text{PCRUDE}) = 0$</p>	<p>Exclusion restrictions. Analysis of $\beta(\text{PCRUDE})$ estimate, CV1 and findings of Babula and Somwaru (1992).</p>	<p>Chi-square value (8df) = 7.9, p = 0.44. Result: Evidence strongly accepts restrictions. $t(\beta(\text{PPROC})) = -0.06$ in CV1 so add as zero reStriction</p>
<p><u>5 in CV2:</u> $\beta(\text{IRAQ1}) = \beta(\text{CROPSPK2}) = \beta(\text{DPOIL07030N}) = \beta(\text{PCRUDE}) = \beta(\text{NEWFBILL}) = 0$, plus: $\beta(\text{PAGCHEM}) = 0$</p>	<p>Exclusion restrictions Identifying restriction based on theory</p>	<p>$t(\beta(\text{CROPSPK1})) = -1.03$ in CV2, so add as zero restriction</p>
Test Set 2: Test Set 1's restrictions plus: $\beta(\text{PPROC}) = 0$ in CV1 & $\beta(\text{CROPSPK1}) = 0$ IN CV2		
<p><u>6 in CV1:</u> Test Set 1's 5 restrictions carried over plus $\beta(\text{PPROC}) = 0$.</p>	<p>Insignificant β-estimate in CV1 during prior estimation.</p>	<p>Chi-square (10 df) = 8.2, p = 0.62). Result: Evidence strongly accepts restrictions.</p>
<p><u>6 in CV2:</u> Test Set 1's 5 restrictions carried over plus $\beta(\text{CROPSPK1}) = 0$.</p>	<p>Insignificant β-estimate in CV2 during prior estimation.</p>	<p>$t(\beta(\text{HIPCRU})) = 1.8$ in CV2 so add as a zero restriction.</p>
Test Set 3: Test Set 2's restrictions plus $\beta(\text{HIPCRU})$ in CV2.		
<p><u>6 in CV1:</u> Test Set 2's 6 restrictions carried over.</p>	<p>Insignificant β-estimate in CV2 during prior estimation.</p>	<p>Chi-square value (11 df) = 10.2, p = 0.51. Result: evidence strong accepts restrictions. The two cointegrating relations are deemed satisfactory.</p>
<p><u>7 in CV2:</u> Test Set 2's 6 restrictions carried over plus $\beta(\text{HIPCRU}) = 0$.</p>		

$$\begin{aligned}
 \text{PFARM} = & 6.93 \cdot \text{PPIALL} + 4.11 \cdot \text{PAGCHEMS} \\
 & (2.6) \quad (2.8) \\
 & - 1.51 \cdot \text{HIPCRU} - 1.39 \cdot \text{CROPSPK1} \\
 & (-5.8) \quad (-6.5) \\
 (6) \quad & + 0.71 \cdot \text{FAIRACT} - 4.5 \cdot \text{DPOIL07} \\
 & (+2.8) \quad (-7.2) \\
 & - 0.02 \cdot \text{TREND}, \\
 & (-4.2)
 \end{aligned}$$

$$\begin{aligned}
 \text{PPROC} = & -0.16 \cdot \text{PPIALL} + 0.0004 \cdot \text{PCRUDE} \\
 & (-2.6) \quad (+4.8) \\
 (7) \quad & + 0.32 \cdot \text{PFARM} - 0.007 \cdot \text{FAIRACT} \\
 & (+22.6) \quad (-2.2) \\
 & + 0.031 \cdot \text{DPOIL07} + 0.001 \cdot \text{TREND}. \\
 & (+3.5) \quad (+17.5)
 \end{aligned}$$

A CV's regressor is weakly exogenous when its statistically significant β -estimate suggests its influence on the error correction or EC mechanism, and its insignificant α -estimate suggests a lack of regressor response to EC adjustments (Juselius 2006). In both equations the $\beta(\text{PPIALL})$ is significant, while the α -estimates (not reported) are insignificant. The general price level's weak exogeneity in both CVs suggests a unidirectional influence on PFARM and PPROC with little appreciable PPIALL adjustment in response to EC movements. This one-way influence on U.S. food-related prices of PPIALL, the movements of which reflect a number of possible macro shocks, coincides with results of Barnett, Bessler, and Thompson (1983, pp. 306–307) and Awokuse (2005, pp. 235–236). The implied elasticity of PFARM response to PPIALL changes of about 7.0 reflects the higher level of PFARM variability over time relative to PPIALL.

As expected, Equation 6's results suggest that farm product prices are positively and significantly tied to movements in the general U.S. price level and agricultural chemical prices. These reduced-form relationships likely arise from positive correlations of PFARM with both movements in rising demand and/or rising production costs that can be associated, in different instances, with PPIALL movements. At first glance there appears to be a surprisingly negative relationship between U.S. farm prices and the binaries of HIPCRU and DPOIL07, two binaries defined for periods of notable recent crude price acceleration. Yet these initially surprising negative estimates coincide

with findings of Haigh and Bessler (2004) and Yu, Bessler, and Fuller (2007), which suggested that, because large proportions of U.S. farm prices are attributed to shipping and transportation costs, there may be negative relationships between U.S. farm prices and shipping costs. As shipping rates increase, reflected by the periods of accelerating crude oil prices, world demand for U.S. farm products ease, suggesting the opposing direction of PFARM adjustment.

As expected, Equation 7's results suggest statistically strong relationships between processed food prices and movements in crude and farm products prices. There appears to be a negative relationship among processed food prices and the general price level, suggesting an elasticity of PPROC response to PPIALL changes of -0.2 . This negative PPROC/PPIALL relationship coupled with a positive PFARM/PPIALL relationship, may suggest a strong demand influence, noted by Capehart and Richardson (2008): rising general prices may elicit a U.S. public shift away from convenience-oriented processed foods (priced with PPROC) toward more staple foods (priced with PFARM) of a less processed nature. Furthermore, the elasticity of PPROC response to changes in farm prices is $+0.3$, and very statistically significant.

References

- Awokuse, T. O. 2005. "Impact of Macroeconomic Policies on Agricultural Prices." *Agricultural and Resource Economics Review* 34(2):226–237.
- Babula, R. A., R. A. Rogowsky, and R. F. J. Romain. 2006. "Exploitation and Analysis of Long Run Cointegration Properties of a Quarterly System of U.S. Wheat-Related Product Markets." *Journal of International Agricultural Trade and Development* (2):241–272.
- Babula, R. A. and A. Somwaru. 1992. "Dynamic Impacts of a Shock in Crude Oil Price on Agricultural Chemical and Fertilizer Prices." *Agribusiness: An International Journal* 8(3): 243–252.
- Barnett, R. C., D. A. Bessler, and R. L. Thompson. 1983. "The Money Supply and Nominal Agricultural Prices." *American Journal of Agricultural Economics* 65(2):303–307.
- Capehart, T. and J. Richardson. 2008. "Food Price Inflation: Causes and Impacts." Congressional

- Research Service (CRS) Report for Congress, Order Code RS22859, Washington DC: CRS. April 10.
- Dennis, H. 2006. *CATS in RATS: Cointegration Analysis of Time Series, Version 2*. Evanston, IL: Estima.
- Estima. 2007. *RATS: Regression Analysis of Time Series, Version 7*. Evanston, IL: Estima.
- Granger, C. and P. Newbold. 1986. *Forecasting Economic Time Series*. New York: Academic Press.
- Haigh, M. and D. A. Bessler. 2004. "Causality and Price Discovery: An Application of Directed Acyclic Graphs." *Journal of Business* 77(4): 1099–1121.
- Johansen, S. 1988. "Statistical Analysis of Cointegration Vectors." *Journal of Economic Dynamics and Control* 12:231–253.
- Johansen, S. and K. Juselius. 1992. "Testing Structural Hypotheses in Multivariate Cointegration Analysis of the PPP and UIP for UK." *Journal of Econometrics* 53:211–244.
- . 1990. "Maximum Likelihood Estimation and Inference on Cointegration: With Applications to the Demand for Money." *Oxford Bulletin of Economics and Statistics* 52:169–210.
- Juselius, K. 2006. *The Cointegrated VAR Approach: Methodology and Applications*. Oxford, UK: Oxford University Press.
- Sims, C. 1980. "Macroeconomics and Reality." *Econometrica* 48:1–48.
- Tiao, G. and G. Box. 1978. "Modeling Multiple Time Series: With Applications." *Journal of the American Statistical Association* 76:802–816.
- U.S. Department of Labor, Bureau of Labor Statistics (Labor, BLS). No date. "Producer price index databases." www.bls.gov. Accessed October 22, 2008.
- Yu, T.-H., D. A. Bessler, and S. W. Fuller. 2007. "Price Dynamics in U.S. Grain and Freight Markets." *Canadian Journal of Agricultural Economics* 55:381–397.