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DYNAMIC ECONOMIC RELATIONSHIPS AMONG U.S. SOY PRODUCT MARKETS: USING A COINTEGRATED VECTOR AUTOREGRESSION APPROACH WITH DIRECTED ACYCLIC GRAPHS

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Dynamic Economic Relationships Among U.S. Soy Product Markets: Using a Cointegrated Vector Autoregression Approach with Directed Acyclic Graphs

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ABSTRACT: This paper applies a combined methodology of a recently developed directed acyclic graph (DAG) analysis with Johansen and Juselius' methods of the cointegrated vector autoregression (VAR) model to a monthly U.S. system of markets for soybeans, soy meal, and soy oil. Primarily a methods paper, Johansen and Juselius' procedures are applied, with a special focus on statistically addressing information inherent in well-known sources of non-normal data behavior to illustrate the effectiveness of modeling the system as a cointegrated multi-market system. Perhaps for the first time, methods of the cointegrated VAR model are combined with DAG analysis to account for contemporaneously correlated residuals, and are applied to this U.S. soy-based system. Analysis of the error correction or cointegration space illuminates the empirical nature of policy-relevant market elasticities, price transmission parameters, and effects of important policy and institutional changes/events on U.S. soy-related markets at long-run horizons beyond a single crop cycle. A statistically strong U.S. demand for soybeans emerged as the primary cointegrating relation in the error-correction space. Analysis of the DAG-adjusted cointegrated VAR model's forecast error variance decomposition illuminates how the soy-related variables and the three U.S. soy product markets dynamically interact at alternative time horizons extending up to two-years.

Key words: Directed acyclic graphs, cointegration, vector error correction and vector autoregression models, monthly U.S. soy-based markets.

Introduction

Prices of soybeans and soy products were, until recently, at record high levels not seen since the 1970s (U.S. Department of Agriculture, Economic Research Service or USDA,ERS, 2004a, b). Since a brief "grain/oilseed crisis" of high and low supplies during the mid-1990s, world grain and oilseed markets have been mostly quiet with low and often declining prices until 2003. However, price volatility returned swiftly during the 2003/04 marketing year,[1] primarily because of three powerful influences (see Babula, Bessler, Reeder, and Somwaru or BBRS 2004, p. 29). First, unfavorable weather stunted the 2002 and 2003 crops in the Northern and Southern hemispheres. Second, there was an escalating Chinese demand for grain and oilseeds for use as raw materials. And third, several serious livestock diseases paralyzed production and trade in meat and related meat byproducts. And while soy and oilseed product prices have declined noticeably since August 2004, effects of oilseed product prices are keenly watched and are of continued interest for these key U.S. commodities (BBRS 2004, p. 29).

We have two purposes. The first is methodological: we combine the methods of the cointegrated vector autoregression or VAR modeling with new and advanced methods of directed acyclic graphs (DAGs) in order to harness information on contemporaneously causal relationships, and apply this method combination to monthly U.S. markets for soybeans, soy meal, and soy oil. This may be the first concurrent application of the cointegrated VAR methods developed by Johansen (1988) and Johansen and Juselius (1990, 1992) and of the methods of DAG analysis of Bessler and Akleman (1998) to the three-market system of U.S. soy-based products.

Our second purpose is to then use the estimated cointegrated VAR model of the U.S. soy product complex mentioned above and obtain a series of policy-relevant econometric results. Such results include crucial market parameter estimates (e.g. the U.S. price elasticity of soybean demand) from an analysis of the long run equilibrium relationships that emerge from the cointegration space, as well as an illumination of the dynamic nature of how soy-based prices and quantities and soy-based markets interact. As well, we exploit the cointegration properties of the model for empirical indications on how statistically important (or unimportant) well-known institutional and policy changes such as the 1995 implementation of the North American Free Trade Agreement (NAFTA) and the 2002 implementation of the current U.S. farm bill (among other events) have influenced market-clearing prices and quantities and the dynamic interactions of the three U.S. soy-based product markets.

This paper extends the work of Babula, Bessler, Reeder, and Somwaru (BBRS, 2004) who used more dated tools and tests, and uncovered evidence that justified the estimation of the same data set as a levels vector autoregression or VAR. We update the set of tools and tests used by BBRS with those of Juselius (2004), and uncovered evidence that also justifies the estimation of BBRS' monthly system of U.S. soy product markets alternatively as a cointegrated VAR.

[1] The "split" year refers to the "crop or market" year. The U.S. crop or market year begins on September 1 and ends August 31 of the ensuing year, such that 2003/04 denotes September 1, 2003 – August 31, 2004. For soy meal and soy oil, the market year starts October 1 and ends September 30 of the ensuing year, such that 2003/04 denotes October 1, 2003 – September 30, 2004.

The remainder of this paper is comprised of eight sections. The first section presents a discussion of time series econometrics, VAR models, and cointegrated VEC models as ways of empirically examining monthly U.S. markets for soybeans, soy meal, and soy oil. As well, the six modeled soy-based market variables are presented, along with the data and data sources. A second section on data analysis examines the model specification implications of harnessing the statistical information inherent in statistically non-normal data. It is well-known that harnessing such information inherent in non-normal behavioral attributes is required for uncompromised inference and in some cases, unbiased regression estimates (Granger and Newbold 1986, pp. 1-5). The third section provides specification of the system as a traditional levels-based VAR model. Following Juselius (2004, chapter 4), effort is expended on achieving an adequately specified levels VAR and its algebraic equivalent, the unrestricted VEC model.[2] This section provides an analysis of results from a battery of diagnostic tests recommended in Johansen and Juselius (1990, 1992) and Juselius (2004, pp. 72-82). Fourth, Johansen and Juselius' (1990, 1992) well-known trace tests and analysis of other relevant evidence are used to determine the reduced rank ("r") of the cointegration space and the number of long run cointegrating relationships, and then restrict the cointegration space for this reduced rank. Fifth, Johansen and Juselius' well-known hypothesis test procedures are applied to the rank-restricted cointegration space to reveal the nature of the long run relationships tying together the upstream and downstream soy-based markets. A sixth section provides an economic interpretation of the cointegrating relations that are fully restricted for rank and for any statistically-supported restrictions that emerged from the hypothesis tests on the cointegration space coefficients. A seventh section follows Bessler and Akleman's methodology and applies DAG analysis to statistically supported patterns of contemporaneous correlations among the fully restricted cointegrated VEC model's innovations (i.e., residuals). We then provide an innovation accounting analysis of the DAG-adjusted cointegrated VEC models' forecast error variance decompositions. These results illuminate the dynamic nature with which soy-based prices and quantities and soy-based markets interact. And finally, a summary and conclusions section follow.

Time Series Econometric Considerations, Modeled Markets, and Data Resources

Since Engle and Granger's (1987) paper, it is well-known that economic time series often fail to meet the conditions of weak stationarity summarized by Granger and Newbold (1986, pp. 1-5). Nonetheless, it is also well-known that while data series are often individually nonstationary, they can form vectors with linear combinations which are stationary, such that the vector of interrelated series are "cointegrated" and move together in tandem as an error-correcting system (Johansen and Juselius 1990, 1992; Juselius 2004). These well-known econometric concepts are summarized, but not detailed here. As demonstrated later, readers should note that most of the modeled soy-based variables defined below are nonstationary: the non-stationary ones are integrated of order-1 or I(1), with the first differences being

[2] This unrestricted VEC is the model before one tests for cointegration, before rank is imposed on the cointegration space, and prior to the imposition of statistically supported coefficient restrictions that emerge from a series of formal hypothesis tests. As in the literature, the cointegrated VAR model and cointegrated VEC model are terms used interchangeably throughout this study.

integrated of order-zero or I(0) and stationary.[3] Six soy-based variables were endogenously modeled, of which four are shown below to be I(1) and two are I(0).

All data are monthly and seasonally unadjusted. A rigorous search of monthly data resources on U.S. soy-based products rendered six variables: price and quantity for soybeans, soy meal and soy oil for the January 1992 – September, 2004 (hereinafter, 1992:01 – 2004:09). Unfortunately, data were not available for periods prior to 1992. The following six variables below are those which we formulate into an unrestricted VAR and ultimately a cointegrated VEC. All data were obtained from the U.S. Department of Agriculture, Economic Research Service (hereinafter, USDA, ERS, 2004a, 2004b) and placed uniformly into metric ton equivalents and natural logarithms before modeling. The variable definitions follow those adapted in recent time series research (BBRS, 2004, pp. 31-32) and include:

1. Market-clearing quantity of soybeans (QBEANS).[4]

2. Farm price of soybeans (PBEANS).

3. Market-clearing quantity of soy meal (QMEAL).

4. Price of soy meal (PMEAL).

5. Market-clearing quantity of soy oil (QOIL).

6. Price of soy oil (POIL).

Analysis of the Soy-Based Time Series Data

Figures 1 through 6 provide the plotted (logged) levels of the modeled data in the upper panels, and data in the first differences of logged levels are plotted in the lower panels. A weakly stationary series has a constant and finite mean and variance, has time-independent observations, and generates regression coefficients that are time-invariant [that is, are not subject to statistical structural change] (Juselius 2004, chapters 3,4). Weakly stationary data typically behave in frequently repeating cycles and frequently mean-revert. A number of data issues clearly arise that preclude weak stationarity and ergodicity required for valid time-series regressions (Granger and Newbold 1986, pp. 1-5).

QBEANS or the market-clearing soybean quantity in figure 1 clearly reflects seasonal effects which may mask an upward trend only minimally evident from the plotted levels.

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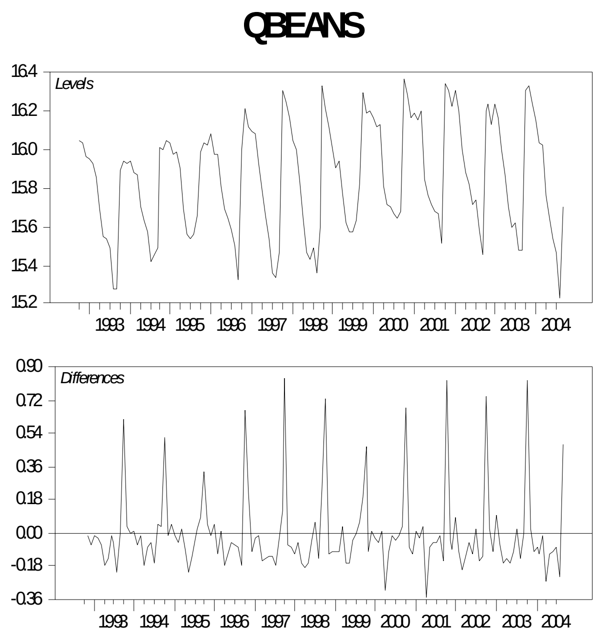
[3] Juselius (2004, pp. 221-223) recommends that the stationarity tests on any single time series be conducted with a chi-square-distributed likelihood ratio statistic within the concept of a modeled system where the cointegration space is restricted for appropriate rank, and not with such univariate tests as those of Fuller (1976) and Dickey and Fuller (1979). Juselius suggests that one take a vector system suspected as cointegrated in levels; obtain an adequately specified levels VAR and equivalent unrestricted VEC; determine the rank of the system; impose the appropriate reduced rank on the cointegration space; and then test each variable's stationarity with a chi-square value (Juselius 2004, pp. 221-223). This is equivalent to testing whether the variable forms a unit vector or a separate cointegrating relationship within the reduced-rank setting. If evidence suggests that all of the endogenous variables are indeed stationary, then one respecifies as a levels VAR.

[4] Readers should note that market clearing quantities of soy meal and soy oil (QMEAL and QOIL) are defined as monthly sums of beginning stocks, production, and imports as production levels are available each month for soy meal and soy oil. QBEANS is defined as the monthly sum of exports, volumes crushed, and ending stocks, which is also the market-clearing quantity. This alternative definition of market-clearing quantity was followed for QBEANS because monthly production figures for U.S. soybeans do not exist.

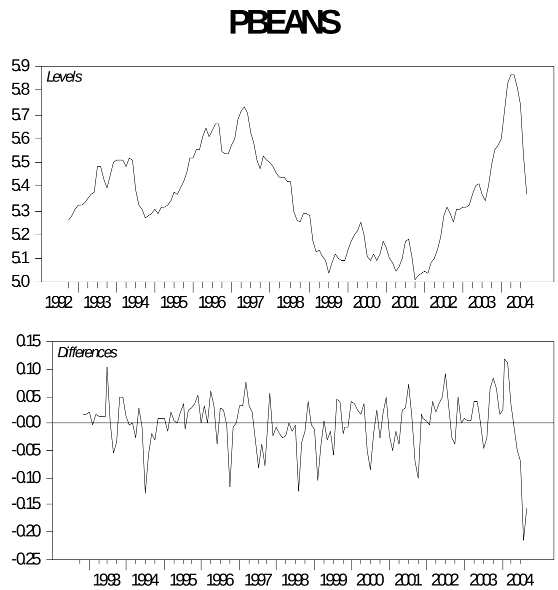
Figure 1's level plots suggest the need for centered seasonal dummy or binary variables, and possibly a linear trend. Figure 1's plotted first differences (hereinafter differences) suggest a potential need to account for marked, non-normal influences of observation-specific events with observation-specific binary variables, especially in 2000 and 2001 (hereafter, outlier observations and outlier binary variables).

Figure 1
Plots of logged levels and differences: QBEANS



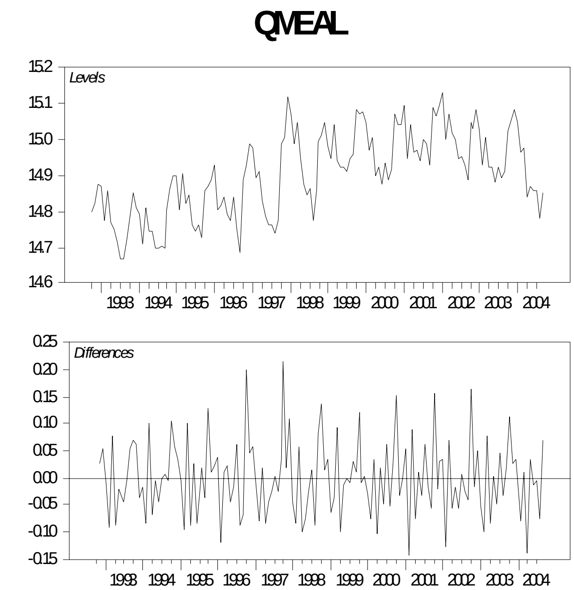
The price of soybeans (PBEANS) in figure 2 suggests several sources of non-normal behavior with model specification implications. The data do not frequently mean-revert and behave in very time-enduring cycles. Changes in level-plot behavior patterns, perhaps from market and policy events addressed below, may suggest time-variance of regression estimates, that is statistical structural change, particularly in the early-1990's and during 1999-2001. PBEANS' levels of variation may change over time (i.e., heteroscedasticity or ARCH effects). Figure 1's levels and differences may reflect non-normal influences of observation-specific outlier events throughout the sample. Outliers appear particularly noticeable in late-2003 and in the early months of 1994 and 1996. Collective specification implications from these behavioral aspects include a number of permanent shift binary variables (to be defined below), a number of appropriately specified outlier binary variables throughout the sample, and the potential inclusion of a linear trend.

Figure 2
Plots of logged levels and differences: PBEANS



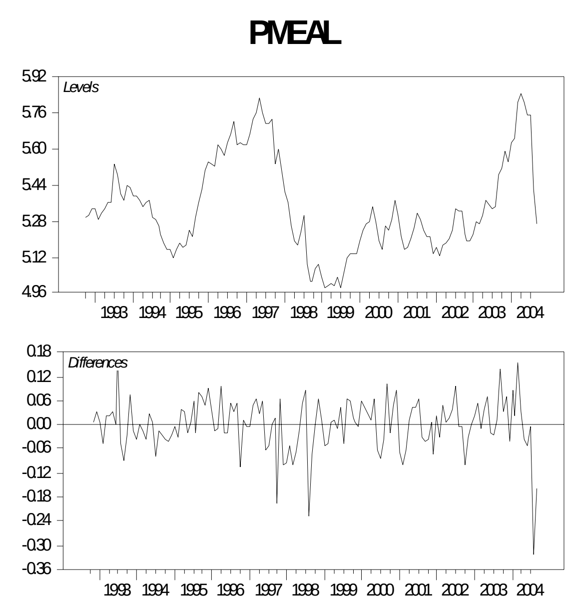
The quantity of soy meal (QMEAL) in figure 3 appears to exhibit statistically non-normal seasonal effects that possibly mask an upward trend, just barely visible to the eye. Variability of the levels appears reasonably constant from the plotted differences, although there may be non-normal and observation-specific outlier effects from the QMEAL plots in 1996, 1997, and during 2001-2002. Specification issues consequently include centered seasonal binary variables, a number of appropriately defined outlier binary variables where appropriate, and a linear trend.

Figure 3
Plots of logged levels and differences: QMEAL



The price of soy meal (PMEAL) in figure 4 exhibits a number of statistically non-normal behavioral characteristics with specification implications. Mean-reversion is infrequent and recurrent data cycles are enduring. Statistical structural change from later-discussed market events and policy changes may well be possible, given the repeated changes in the slope of PBEANS in several subsamples of the estimation period. As well, the plotted PMEAL differences in figure 4 suggest the potential need for observation-specific binary variables to capture extraordinary outlier events, particularly at the sample's very end and during 1997-1998. Specification considerations include a set of permanent shift binary variables to capture influences of a number of market and policy/institutional events discussed

Figure 4
Plots of logged levels and differences: PMEAL



below; a number of appropriately defined outlier binary variables for particularly important observation-specific events; and a linear trend.

The quantity of soy oil (QOIL) in figure 5 and the price of soy oil in figure 6 displays a number of statistically non-normal behavioral attributes. Levels seldom mean-revert, and behave in time-enduring cycles. And a linear trend is possible. There are a number of subsample changes in slope, which may suggest structural change from a number of market events and policy changes. Specification considerations include binary variables to account for effects of important events and policy changes, and also a linear trend.

Figure 5
Plots and differences of logged levels: QOIL

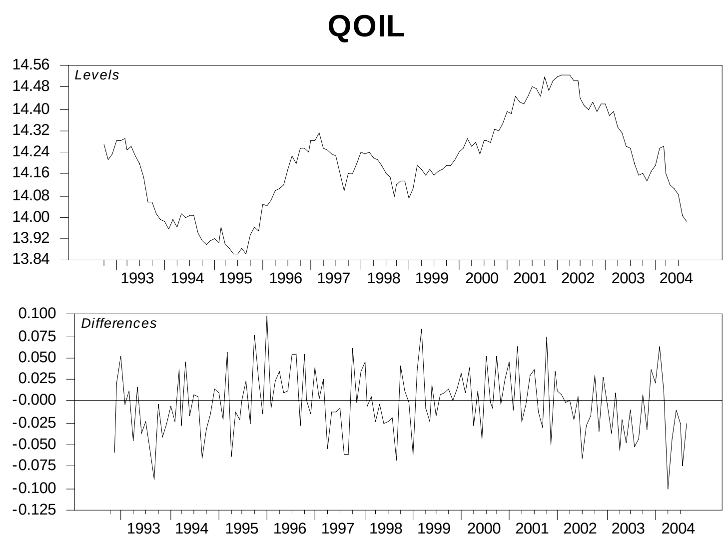
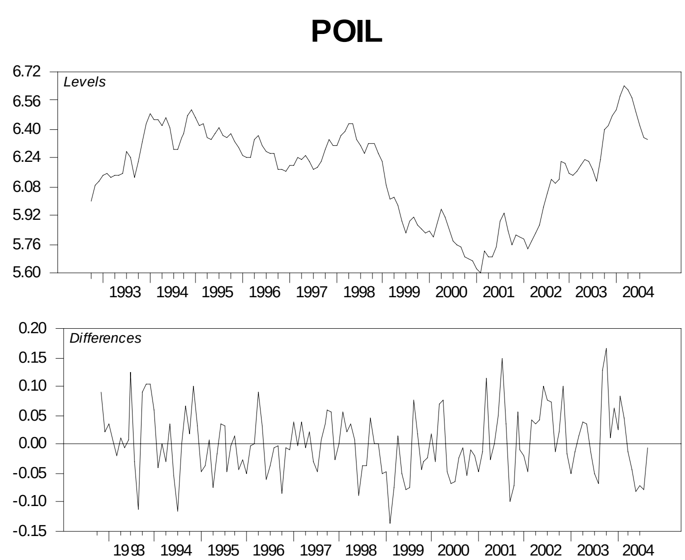


Figure 6
Plots of logged levels and differences: POIL



The Statistical Model: The Unrestricted Levels VAR and VEC Equivalent[5]

Throughout, a number of terms are used: (1) the *unrestricted levels VAR* denotes a VAR model in logged levels; (2) the *unrestricted VEC* denotes the algebraic equivalent of the unrestricted levels VAR in error correction form, where the levels component (cointegration space) is not yet restricted for rank or for statistically supported restrictions; (3) the *cointegrated VEC* is the unrestricted VEC just mentioned where the cointegration space has been restricted for reduced rank; and (4) the *fully restricted cointegrated VEC* is the unrestricted VEC after the cointegration space's restriction for reduced rank and for the statistically supported restrictions on cointegration space coefficients that emerge from the hypothesis tests. As well, "p" denotes the number (six) of endogenous variables; "p1" denotes the number of variables in the cointegration space (six endogenous and various deterministic variables introduced later); and "r" represents the cointegration space rank (and number of cointegrating relationships). Our methods involve specification and estimation of an adequately specified unrestricted levels VAR (and its algebraic equivalent, an unrestricted VEC), such that residual behavior approximates well-known assumptions of multivariate normality (Juselius 2004, chapter 5).

The Levels VAR and unrestricted VEC of the soy-based market system.

Bessler (1984) notes that a VAR model posits each endogenous variable as a function of k lags of itself and of each of the remaining endogenous variables in the system. The above six variables render the following unrestricted, six-equation VAR model in logged levels:

$$
\begin{aligned}
(1)\ X(t) = {} & a(1,2)*QBEANS(t-1) + \ldots + a(1,k)*QBEANS(t-k)+ \\
& a(2,1)*PBEANS(t-1)+ \ldots +a(2,k)*PBEANS(t-k)+ \\
& a(3,1)*QMEAL(t-1) + \ldots +a(3,k)*QMEAL(t-k)+ \\
& a(4,1)*PMEAL(t-1)+ \ldots +a(4,k)*PMEAL(t-k)+ \\
& a(5,1)*QOIL(t-1)+ \ldots +a(5,k)*QOIL(t-k) + \\
& a(6,1)*POIL(t-1)+ \ldots +a(6,k)*POIL(t-k)+ \\
& a(c)*CONSTANT + a(S)* SEASONALS + \epsilon(t)
\end{aligned}
$$

The asterisk denotes the multiplication operator throughout. The $\epsilon(t)$ is a vector of residuals distributed as white noise. X(t) = QBEANS(t), PBEANS(t), QMEAL(t), PMEAL(t), QOIL(t), and POIL(t). The a-coefficients are ordinary least squares (OLS) estimates with the first parenthetical digit denoting the six endogenous variables as ordered above, and with the second referring to the lags 1, 2, ... , k. The a©) is the coefficient on the intercept. The parenthetical terms on the endogenous variables refer to the lag, with t referring to the current period-t, and t-k referring to the kth lag. The a(S) is a vector of coefficient estimates on the centered seasonal variables.

As suggested by Juselius (2004), the lag structure was chosen based on a likelihood ratio test procedure – chosen here as Tiao and Box's (1978) procedure. Results suggested a two-order lag (k=2), and throughout, the unrestricted VAR model is denoted as the VAR(2) model. Market year data is available from 1992:10 – 2004:09, and given the k=2 lag structure, the estimation period was 1992:12 – 2004:09.

[5] This section draws heavily on the work of Johansen and Juselius (1990, 1992) and Juselius (2004).

Johansen and Juselius (1990) and Juselius (2004, p. 66) demonstrated that the above VAR(2) model in equation 1 is now rewritten more compactly in the algebraically equivalent unrestricted VEC form of equation 2:

(2) $x(t) = \Gamma(1) * \Delta x(t-1) + \Pi * x(t-1) + \Phi * D(t) + \epsilon(t)$, $\epsilon(t)$ distributed as white noise.

The x(t) and x(t-1) are p by 1 vectors of the above six soy-related variables in current and lagged levels, $\Gamma(1)$ is a p by p matrix of short run regression coefficients on the lagged variables, and Π is a (p by p) error correction term to account for the six endogenous variables. The Φ*D(t) is a set of deterministic variables: 11 seasonals and a host of other trend and dummy variables which will be added to address the data issues identified above as the analysis unfolds. The rank-unrestricted Π or error correction term is decomposed as follows:

(3) $\Pi = \alpha * \beta'$ where α is a p by r matrix of adjustment speed coefficients and β is a p by r vector of error-correction coefficients.

The $\Pi = \alpha * \beta'$ term is interchangeably denoted as the levels-based long run component, error correction term, or cointegration space of the model. The [Δx*(t-1), Φ*D(t)] is collectively considered the short run/deterministic model component.

The data analysis above suggested a number of considerations for specifying the long run and the short run/deterministic components in equation 2. Inclusion of a linear trend (TREND) and various permanent shift binary variables (defined below) were considered for the cointegration space components. These same variables in differenced form as well as the 11 centered seasonal binary variables were considered for inclusion in the model's short run/deterministic component. Analysis below will also lead to consideration, where appropriate, of various and appropriately specified outlier binary variables in the model's short run/deterministic component.

The data analysis, consultation with various expert soy product market analysts, and previous research by BBRS (2004) gave rise to the definition of the following nine permanent shift dummy variables for possible inclusion in the levels-based cointegration space and in differenced form in the short run/deterministic model component (hereafter denoted by the upper-cased label of introduction).

URUGUAY: valued at unity from January, 1994 and 0.0 otherwise to capture effects of the implementation of the Uruguay Round of the WTO trade negotiations.

NAFTA: valued at unity from January, 1995 to present and 0.0 otherwise to capture the effects of the implementation of the North American Free Trade Agreement among the United States, Canada, and Mexico.

FLOOD93: valued at unity from May 1993 through August 1993, and 0.0 otherwise, to account for the adverse production and yield effects from massive floods in the U.S. Midwest.

SPIKE95: valued at unity from May 1995 through August 1997, and zero otherwise, to account for the influences of the higher prices and demand levels for oilseeds worldwide.

WEATHER95: valued at unity from September 1994 through August 1996 to account for the positive effects on U.S. soybean production and yields from a period of extraordinarily favorable weather.

FAIRACT: valued at unity from September 1997 through August 2003, and 0.0 otherwise, to account for the soy product market effects of the 1996 Farm Bill (i.e., "Fair Act").

NEWFBILL: valued at unity from September 2002 through September 2004 (or sample's end) and 0.0 otherwise to capture soy market impacts of the most recent and current U.S. farm bill.

HIDEMAND: valued at unity from February 2003 through July, 2004 to account for the period of unusually high world prices and demand levels for soybeans and soy products as detailed in BBRS (2004, pp. 29-32).

MADCOW: valued at unity from January 2004 through July 2004 to account for high soy product prices and demand levels from a demand shift towards such products as livestock feed ingredients after the December 2003 discovery of bovine spongiform encelopathy (hereinafter, BSE or mad cow disease) in Washington State (see analysis by BBRS 2004, pp, 29-32).

The initial starting point for the unrestricted VEC was equation 2 with only the seasonal variables included in the short run/deterministic component of the model. A well-specified unrestricted VEC was ultimately achieved in a series of sequential estimations. These estimations added a linear trend, seven demand shift binary variables (of the nine defined above), and various other binary variables associated with month-specific events – one variable for each estimation. A variable was added and retained if it generated a movement in patterns or directions of a battery of statistical diagnostic values indicative of improved specification. Following Juselius' (2004, chapters 4, 7, and 9) recommendations, the array of diagnostics includes: (a) trace correlation as an overall goodness of fit indicator, (b) likelihood ratio test of autocorrelation for the system, (c) system-wide and univariate Doornik-Hansen tests for normality, (d) indicators for skewness and kurtosis, and (e) univariate tests for heteroscedasticity (i.e., ARCH effects). The successive or "sequential" estimations were ceased when the series of diagnostic values stabilized and failed to favorably move with inclusions of additional binary variables. After achievement of an adequately specified levels VAR and unrestricted VEC, a test for parameter constancy was performed to discern if there were problems with time-variance of estimated parameters (i.e., statistical structural change).

The sequential estimations were implemented in two basic sets. The first set focused on including, one by one, the above-mentioned permanent shift binary variables (and a linear trend) in the long run component and in differenced form within the short run/deterministic component of equation 2. Ultimately, eight were included [6] in the long run components and in differenced form in the short run/deterministic component of equation 2.

The second set of sequential estimations aimed to further improve specification obtained from the unrestricted VEC with the eight just-cited variables. More specifically, the second set of sequential estimations captured extraordinary, non-normal influences of observation-specific events through the use of transitory ("outlier") binary variables. Each time a potential outlier was considered indicative of a extraordinary effects because of a "large" standardized residual,[7] an appropriately specified variable was

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[6] The eight included variables are TREND, NAFTA, URUGUAY, FAIRACT, NEWFBILL, HIDEMAND, MADCOW, and SPIKE95.

[7] We followed a procedure for examination and analysis of potential outlier events using "outlier" binary variables (see Juselius 2004, chapter 6). An observation-specific event was judged as an "extraordinary" one if it generated a standardized residual of about 3.6 or more. More specifically, such a criterion for outliers was designed based on the sample size using the Bonferoni criterion: INVNORMAL$(1.0\text{-}1.025)^{144}$, where INVNORMAL is a function for the inverse of the normal distribution function that returns the variable for the c-density function of a

included in equation 2's short run/deterministic component, and ultimately retained if the battery of monitored diagnostic values moved in favorable patterns indicative of improved specification. Three observation-specific outlier binaries were included: DTR9809, DTR9901, and DTR0109.[8]

An adequately specified model should generate residuals that behave with approximate statistical normality. Table 1 provides an array of diagnostic values focused on specification for two estimations: the initially estimated unrestricted VEC before sequential estimations aimed at improved specification (with only seasonal binary variables) and for the unrestricted VEC judged as adequately specified after inclusion of the trend, seven permanent shift binary variables, three outlier binary variables, and seasonals. Table 1's results demonstrate clear improvements in achieving acceptable specification and in generating residuals that behave with approximate statistical normality.[9] These results clearly demonstrate noticeable specification improvements and the benefits of focusing intense scrutiny on the properties of the modeled series – properties which Juselius maintains are often not adequately considered.[10]

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standard normal distribution (see Estima 2004, RATS Version 6, p. 503). Here, the Bonferoni variate equals about 3.6 for the sample size of T=144. All observations with standardized residuals with an absolute value of about 3.6 or more were considered indicative of potentially extraordinary outlying events. Each outlier binary was then placed into equation 2's short run/deterministic component, a separate estimation of the model was implemented for each binary, and the outlier binary variable was retained if there was favorable movement in the grid of diagnostic values indicative of improved specification.

[8] The outlier "blip" binary variables appeared to reflect market disturbances which commenced in 1998:09 for DTR9809; in 1999:01 for DTR9901, and in 2001:09 for DTR0109. Influences associated with DTR9808 and DTR9901 were likely associated with the phased influences on the U.S. soy product markets associated with the 1996 U.S. farm bill (FAIR Act). Influences associated with DTR0109 are likely the result of the then-anticipated provisions of the current U.S farm bill. PMEAL levels fell markedly for two consecutive months (1998:08, 1998:09) leading to a differenced binary variable DTR9809 of the following form for equation 2's short run/deterministic component: value of unity for 1998:08; of zero for 1998:09, and of -1.0 for 1998:10, and a zero value otherwise. QOIL fell for one month in 1999:01, having led to a differenced binary variable, DTR9901, of the following form for equation 2's short run/deterministic component: unity value for 1999:01, -1.0 value for 1999:02, and a zero value otherwise. POIL levels dropped for two consecutive months in 2001:09 and 2001:10, having led to a differenced binary variable, DTR0109, of the following form for inclusion in equation 2's short run/deterministic component: unity for 2001:09, zero for 2001:10, and -1.0 for 2001:11, and a zero value otherwise.

[9] Each equation for the levels VAR(2) and its unrestricted VEC algebraic equivalent was estimated over the 1992:12-2004:09 sample period, about 13 market years. There were 144 observations in the estimation period; 142 observations after imposing the two-lag structure; and 118 degrees of freedom.

[10] Dr. Katarina Juselius made this point during an econometrics course on cointegration methods. The point is that many applications of time series econometric methods are done without getting an adequate handle on the properties of the modeled data series. One of our primary aims was to present the diagnostic results in table 1 and show the value of considering the data's behavioral properties when specifying VAR and VEC models. The course: "Econometric Methodology and Macroeconomic Applications, the Copenhagen University 2004 Econometrics Summer School," instructed by Drs. Katarina Juselius, Soren Johansen, Anders Rahbek, and Heino Bohn Nielsen, August 2-22, 2004, Institute of Economics, Copenhagen University, Denmark.

Table 1
Mis-specification Tests for the Unrestricted VEC: Before and After Specification Efforts

Test and/or equation	**Null hypothesis and/or test explanation**	**Prior efforts on specification adequacy**	**After efforts on specification adequacy**
Trace correlation	system-wide goodness of fit: large proportion desirable	0.52	0.65
ARCH tests for heteroscedasticity (lags 1, 4)	Ho: no heteroscedasticity by 1st, 4th lag for system. Reject with p-values less 0.05	lag 1: 35.6 (p=0.49) lag 4: 24.5 (p=0.93)	lag 1: 46.8 (p=0.11) lag 4: 22.0 (p=0.97)
Doornik-Hansen test, system-wide normality	Ho: modeled system behaves normally. Reject for p-values below 0.05.	26.6 (p=0.01)	6.12 (p=0.91)
Doornik-Hansen test for normal residuals (univariate)	Ho: equation residuals are normal. Reject for values above 9.2 critical value		
ΔQBEANS		3	0.59 (*)
ΔPBEANS		17.4	1.51(*)
ΔQMEAL		0.21	0.51
ΔPMEAL		9.41	1.1 (*)
ΔQOIL		3.15	0.89
ΔPOIL		2.5	2.1
Skewness(kurtosis) univariate values	skewness: ideal is zero; “small” absolute value acceptable kurtosis: ideal is 3.0; acceptable is 3-5.		
ΔQBEANS		-0.12 (3.0)	0.44 (3.97)
ΔPBEANS		-0.05 (4.7)	-0.20 (3.2)
ΔQMEAL		-0.09 (2.8)	0.14 (2.9)
ΔPMEAL		-0.23 (4.2)	0.21 (2.99)
ΔQOIL		0.05(3.5)	-0.017 (3.1)
ΔPOIL		0.30 (2.5)	-0.29 (2.99)

Notes.– An asterisk (*) denotes a favorable movement (decline) in the relevant test/diagnostic value into the range of statistical normality.
Source: Generated by Doan’s (2004) software diagnostic test applications to the model estimated by Commission staff.

Evidence suggests that efforts at achieving specification increased the model's ability to explain system behavior by about 25 percent, with the trace correlation, a system-wide goodness-of-fit indicator, having risen from 0.52 to 0.65 (table 1). ARCH effects at the first and fourth lags were not a problem.

With a null hypothesis of system-wide behavior that is statistically normal, the Doornik-Hansen value, distributed as a chi-squared variable (12 degrees of freedom), suggests a notable shift in the system's residuals towards statistically normal behavior. The D-H value of 26.6 (p-value = 0.01) for the initial model before efforts at specification adequacy suggested that evidence at the 5-percent level was sufficient to reject the null hypothesis that residuals behaved with statistical normality. With an D-H value of 6.12 and a p-value of 0.96, evidence was insufficient to reject the null that the modeled system's residuals after specification efforts behaved normally. This D-H value's reduction in table 26.1 to 6.1 is a noticeable improvement.

Improvement in single-equation residual behavior towards statistical normality is also evident from table 1's univariate D-H and p-values. One fails to reject the null hypothesis that an equation's residuals behave normally when its univariate value falls below the 9.2 critical chi-square value (5-percent, two degrees of freedom). Prior to efforts on specification, two of the six single-equation D-H values exceeded 9.2 and suggested non-normal behavior: the ΔPBEANS and ΔPMEAL. After specification efforts, all six equation-specific values in table 1 fell below the 9.2 critical value and suggested evidence of residual behavior that is approximately statistically normal. Such declines were particularly noticeable for ΔPBEANS and ΔPMEAL. The system and univariate D-H tests suggests evidence that supports statistically normal residual behavior.

Table 1 also provides indications on skewness and kurtosis of each equation's residuals. Normal behavior from adequate specification suggests that skewness should be as near to zero as possible, with (absolute) values of unity or less generally considered acceptable (Juselius 2004, chapter 4). For normally behaving residuals, a kurtosis value of 3.0 would be optimal, with a range of 3.0 – 5.0 considered reasonable (Juselius 2004, chapter 4). Table 1 suggests that after specification efforts, residual skewness (absolute) values ranged from 0.14 to 0.29, while kurtosis values ranged from 2.9 to 3.1, both ranges considered indicative of approximately normal residual behavior for all six equations.

Following Juselius' (2004, chapter 4) procedures, we deemed the diagnostics for the unrestricted VEC after efforts to enhance specification as indicative of those of a reasonably and adequately specified model. The success of efforts to improve specification was particularly evident from the favorable movements in table 1's trace correlation and the Doornik-Hansen test values.

Cointegration: Determining and Imposing Reduced Rank the Error Correction Space

Juselius (2004, p. 86) notes that cointegration implies that there are six individually nonstationary variables that are integrated of an order lower than itself. Cointegrated variables that are integrated of order-1 or I(1), that is individually nonstationary, share common stochastic and deterministic trends and tend to move in tandem through time in a stationary manner (Johansen and Juselius 1990, 1992; Juselius 2004, p. 86).

Reconsider the unrestricted VEC in equations 2 and 3. Insofar as x(t) and x(t-1) are I(1) or nonstationary, then Δx(t-1) must be nonstationary or I(0). There are three possible settings where equation 2 can hold:

- First, the rank of Π is zero , whereby the entire levels-based long run component is zero; the six soy-based variables do not share common trends and do not move together over time; and a VAR in first differences would be appropriate. Analysis of figures 1-6 render this setting as unlikely.

• Second, the rank of Π could be full (p =6 = r), whereby the system is fully stationary and the six variables would be appropriately modeled as a VAR in levels (as equation 1). This also is clearly not the case as evidence from the data analysis and from test results below suggests that most of the variables are I(1) in logged levels.

• And third, the rank of Π is reduced , r < p, and ranges from 1 to 5. In this case, equation 2 could hold even if all or most of the six series are individually I(1), as the levels-based long run component would be non-zero but nonetheless stationary (Juselius 2004, pp. 86-87). This third case reflects cointegration.

Under the third case, β'*x(t) is stationary or I(0). Determination of the reduced rank is a three-tiered process. First, one conducts the trace tests summarized in Johansen and Juselius (1990, 1992). Second, rank-relevant information emerging from an examination of the companion matrix's unit roots should be considered. And third, an inspection of the plotted cointegrating relations are examined for stationarity properties.

Nested Trace tests and Other Evidence for Rank Determination of Π

Table 2 provides trace test evidence for rank determination. The 95-percent fractile values are adjusted for the restriction of seven permanent shift binary variables to lie in the cointegration space (see Juselius 2004, chapter 8). Tests are nested and one should begin atop of the table. Evidence at the 95 percent significance level is sufficient to reject the first three nested null hypotheses. Evidence is only marginally sufficient to reject the null hypothesis that the rank is less than or equal to 4 as both the trace and fractile values are nearly equal. The trace values reject the hypothesis that the rank is four or less. Given the borderline nature of the evidence in failing to reject the null that Π's rank is four or less, we follow Juselius (2004, chapter 8) and fail to place sole reliance on the trace test evidence, and consider additional rank-relevant evidence.

Table 2
Trace test statistics and related information for nested tests for rank determination

Null Hypothesis	Trace Value	95% Fractile (critical value)	Result
rank or r ≤ 0	267.8	130.1	Reject null that rank is zero.
rank or r ≤ 1	167.2	101.2	Reject null that rank or r ≤1
rank or r ≤ 2	107.6	76.3	Reject null that rank or r ≤ 2
rank or r ≤ 3	67.3	55.4	Reject null that rank or r ≤ 3
rank or r ≤ 4	38.7	38.3	Marginally reject null that rank or r ≤ 4
rank or r ≤ 5	17.1	25.1	Fail to reject that rank or r ≤ 5

Notes.– As recommended by Juselius (2004, p. 171), CATS2-generated fractiles are increased by 7*1.8 or 12.6 to account for the 7 permanent shift binary variables restricted t lie in the cointegration relations.
Source: Generated by Doan's (2004) software diagnostic test applications to the model estimated by Commission staff.

Table 2's results suggest that the rank is four or less. Yet information concerning the characteristic roots in table 3 when r is set at 3 suggests that r is 3 instead of 4. If r=3 is an appropriate choice of reduced rank for the error correction term, then there should be three unity-valued characteristic roots with the fourth being statistically sub-unity.[11] The fourth root is 0.78, which we deem to probably be adequately “small,” and is likely more statistically sub-unity than unity.[12]

Following Juselius (2004, pp. 174-175), we peruse plotted graphs of the first four cointegrating relationships for evidence of stationarity. In our case, if the first three relations appear stationary, and the fourth nonstationary, then Juselius (2004, pp. 174-175) contends that this is evidence supporting the choice of rank r=3 as appropriate. The unrestricted VEC’s first four cointegrating relations are in figures 7-10. The BETA*x(t) plots were generated by the model incorporating short run effects, while the BETA*R1(t) plots were generated by the model corrected for short run effects. Juselius (2004, pp. 174-175) prefers the BETA*R1(t) plots as the most reliable.

The first two cointegrating relation plots in figures 7 and 8 reflect elements of stationary behavior: mean-reversion; short, frequent behavioral cycles; generally constant levels of variation; reasonably constant mean; and a lack of trending. Figure 9's plot of the third relation exhibits more extended cycling above and below the mean and perhaps more ARCH effects than the plotted relations in the previous two figures. Nonetheless, aside from the 1996-1998 and 2002-2003 subperiods, figure 9's plotted depiction of the third cointegrating relation seems to display basic elements of stationary behavior.

Table 3.
Roots of the Companion Matrix, Rank = 3

	Real	Imaginary	Modulus	Argument
Root1	1.0000	0.0000	1.0000	0.0000
Root2	1.0000	0.0000	1.0000	0.0000
Root3	1.0000	-0.0000	1.0000	-0.0000
Root4	0.7808	0.0000	0.7808	0.0000
Root5	0.5353	0.1256	0.5499	0.2304
Root6	0.5353	-0.1256	0.5499	-0.2304
Root7	0.3097	0.3550	0.4711	0.8534
Root8	0.3097	-0.3550	0.4711	-0.8534
Root9	0.4025	0.0000	0.4025	0.0000
Root10	-0.1700	-0.3444	0.3840	-2.0293
Root11	-0.1700	0.3444	0.3840	2.0293
Root12	-0.2732	0.0000	0.2732	3.1416

Source: Generated by Doan’s (2004) software.

[11] If r=4 was incorrectly imposed when r was in reality 3, then the fourth root would be statistically more unity than sub-unity, that is would be “large” and r should be reduced from 4 from 3. If r=3 is imposed when three is the appropriate rank, then the fourth root would be statistically sub-unity. See Juselius (2004, chapter 8).

[12] And perhaps while this may seen an arbitrary conclusion, the conclusion certainly would have been more guarded, if made at all, had the fourth root been 0.90 or more.

Figure 7
Plotted cointegrating relation 1: versions with and without correction for short run effects

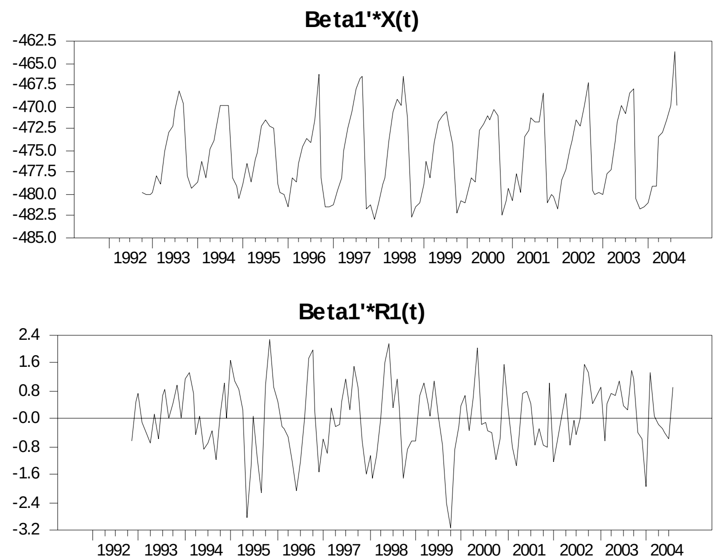


Figure 8
Plotted cointegrating relation 2: versions with and without correction for short run effects

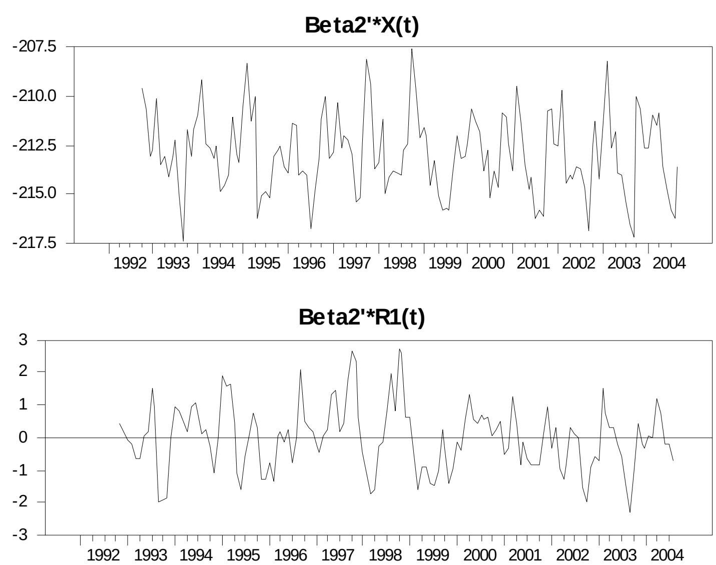


Figure 9
Plotted cointegrating relation 3: versions with and without correction for short run effects

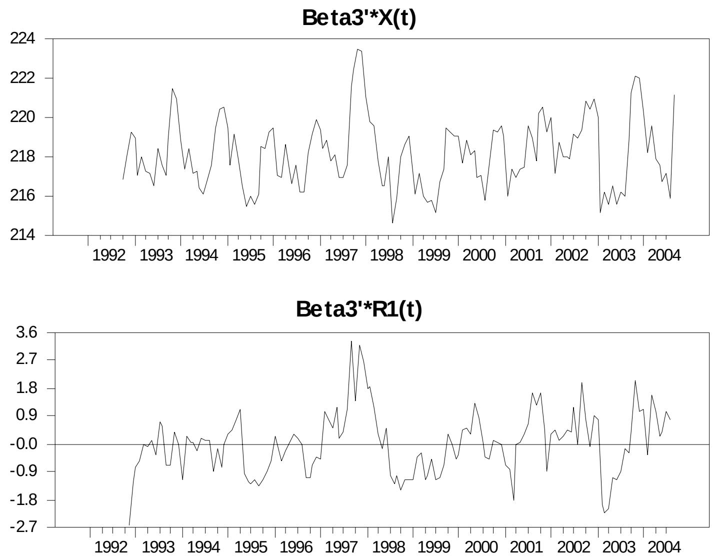
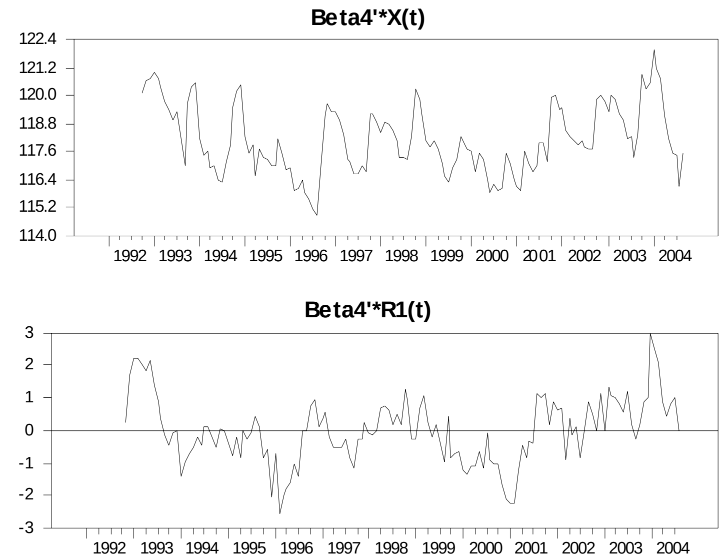


Figure 10 plots the fourth cointegrating relation, that displays clearer elements of nonstationary behavioral elements than the previous three plotted relations, particularly in the panel of BETA*R1(t) plot. There are extended cycling of values in substantial parts of the sample: at the sample's very beginning and very end, as well as during 1995-1996 and 1999-2001. As well, the fourth relation's plot seems heteroscedastic. Generally, figure 10 suggests that the fourth relation is non-stationary and this suggests that perhaps the rank is 3.

As cautioned by Juselius (2004, pp. 172-176), choice should not be made with sole reliance on trace test evidence. In summary, r=3 appears more supported than r=4 as a rank for equation 2's Π when one considers all combined evidence from the trace tests, the companion matrix's characteristic roots when a rank of 3 is imposed, and an analysis of plotted behavior patterns of these first four cointegrating relationships. We chose to impose a rank of r=3 on the error correction space.

Figure 10
Plotted cointegrating relation 4: versions with and without correction for short run effects

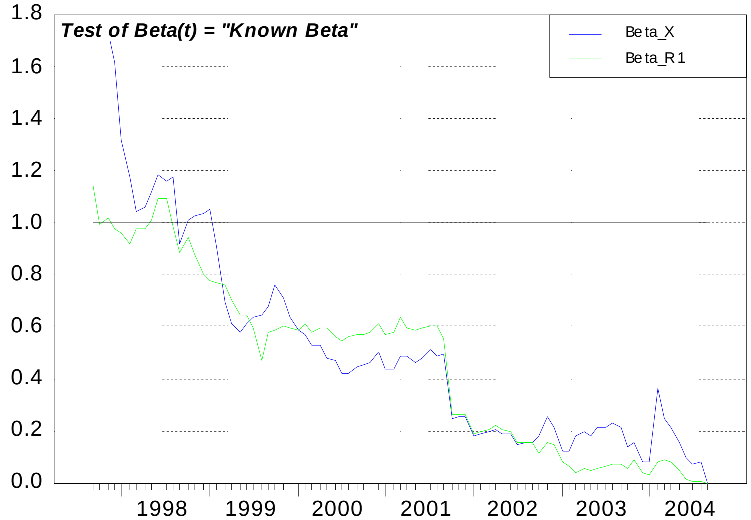


Test for Parameter Constancy.

Figure 11 provides the recursively calculated "known beta" test of parameter constancy provided by CATS2 software and detailed in Juselius (2004, pp. 186-190). This test is typically implemented on the adequately specified and rank-restricted (here with r=3) VEC model before the series of hypothesis tests. This known beta method tests if there is constancy of estimated cointegration space estimates. This test examines if the full sample ("baseline") model's cointegration space coefficients could have been accepted as those of each model recursively estimated over the 1997:09 – 2004:09 period.[13] The plotted known-beta values in figure 11 are for two model versions: corrected and not corrected for short run effects (BETA_X and BETA_R1). Juselius (2004, pp. 186-190) recommends placing more reliance on the BETA_R1 plot. The known-beta values are indexed by the 95 percent critical value, and should ideally be unity or less to indicate parameter constancy (Juselius 2004, pp. 186-190). Because most of the values in both the BETA_X(t) and BETA_R1 plots are unity or less, we follow Juselius (2004, pp. 186-190) and conclude that evidence at the 95 percent significance level is insufficient to reject the hypothesis of no structural change. Evidence suggests that the estimated parameters are time-invariant.

[13] This subsample of recursive estimation, 1997:09 – 2004:09, is for the period beginning with the 1997/98 U.S. soybean marketing year and extending through the estimation period's end. The finally restricted VEC regressors required 44 degrees of freedom from 1992:12, the effective estimation period starting point with the two lag structure. The three cointegrating relationships that emerged from the rank-restricted, adequately specified VEC are provided as 4, 5, and 6.

Figure 11
Recursively calculated "known beta" test of parameter constancy



The test statistic is scaled by the 5% critical value

Equations 4-6 are the three cointegrating relationships which emerged from imposing rank after using Johansen and Juselius' (1990, 1992) well-known reduced-rank estimator. These estimates are not yet restricted for evidentially supported economic restrictions which emerge from the next section's hypothesis tests.

(4) QBEANS = -0.94*PBEANS - 1.55*QMEAL + 0.55*PMEAL + 0.05*POIL + 0.03*NAFTA + 0.15*URUGUAY
+ 0.09*FAIRACT + 0.10*NEWFBILL -0.03*HIDEMAND -0.15*MADCOW - 0.12*SPIKE95 = 0.002*TREND

(5) QMEAL = -0.05*PMEAL + 0.39*QBEANS + 0.03*PBEANS + 0.12*QOIL + 0.08*POIL - 0.01*NAFTA
+0.08*URUGUAY + 0.06*FAIRACT + 0.003*NEWFBILL + 0.03*HIDEMAND - 0.012*MADCOW
+ 0.08*SPIKE95 - 0.00001*TREND

(6) PMEAL = -0.87*QMEAL - 0.01*QBEANS + 0.94*PBEANS + 0.26*QOIL - 0.55*POIL + 0.10*NAFTA
+ 0.02*URUGUAY + 0.01*FAIRACT - 0.04*NEWFBILL + 0.25*HIDEMAND + 0.14*MADCOW
+ 0.08*SPIKE95 + 0.001*TREND

Hypothesis Tests and Inference on the Economic Content of the Three Cointegrating Relations

Our procedure begins with equations 4 – 6, the three unrestricted cointegrating relations, and we conduct a series of hypothesis tests on the $\Pi = \alpha'^{*}\beta$ or error-correction matrix, and then impose those restrictions which are statistically supported by the hypothesis test evidence (Juselius 2004, chapter 10). Johansen and Juselius (1990, pp. 194-206) and Juselius (2004, chapter 10) detail these procedures.

Hypothesis tests on the beta coefficients take the form:

(7) $\beta = H^*\varphi$

Above, β is a p1 by p1 vector of coefficients on variables included in the cointegration space; H is a p1 by s design matrix, with "s" being the number of unrestricted or free beta coefficients; and φ is an s by r matrix of the unrestricted beta coefficients (Juselius 2004, pp. 245-248). Johansen and Juselius' (1990, 1992) well-known hypothesis test value or statistic is provided in equation 8.

(8) $-2\ln(Q) = T^*\sum[(1-\lambda_i^*)/(1-\lambda_i)]$ for I = 1, 2, and 3 (=r).

The asterisked (non-asterisked) eigenvalues (λ_i , i = 1-3) are generated by the model estimated with (without) the tested restriction(s) imposed.

Likewise, the hypothesis tests concerning the α or adjustment speed coefficients permit a characterization of relative speeds of error-correcting adjustment with which the system responds to a given shock (Johansen and Juselius 1990, 1992; Juselius 2004, chapter 11). The null hypothesis or H(0) is:

(9) H(0): $\alpha = A^*\psi$

Above, A is a p by s design matrix; s is the number of unrestricted coefficients in each of the r=3 columns of the α matrix; and ψ is the s by r matrix of the non-restricted or "free" adjustment speed coefficients (Juselius 2004, chapter 11). Equation 9's test statistic also applies here, and is distributed asymptotically as chi-squared distribution with degrees of freedom equal to the number of imposed coefficient restrictions (Juselius 2004, pp. 206-207 and 211-213). Three sets of hypothesis tests on the betas, followed by tests on the alphas, are provided below.

Hypothesis Tests on the Betas.

There are three sets or groups of hypothesis tests on the beta coefficients. The first group of six examines if each endogenous variable is stationary under the imposed rank of three. Second, given that each of the cointegrating relations has p1 or 14 variables,[14] there are 14 "exclusion hypotheses" of whether each variable is zero in the three cointegrating relations. Given the results of these two sets of tests, a third set of sequential hypothesis tests on the individual beta estimates is provided on equations 4, 5, and 6, with any statistically supported stationarity and/or exclusion restrictions imposed.

Tests of Stationarity

Juselius (2004, pp. 220-222) recommends a system-based likelihood ratio test of each endogenous variable's stationarity, and given the imposed rank (here r=3). She recommends such a test over univariate stationarity tests (e.g. Dickey-Fuller tests) which are independent of the cointegrated system's chosen rank. Basically, the recommended likelihood ratio tests examine whether each endogenous variable itself constitutes a separate stationary cointegrating relation, with a unity value for

[14] The 14 variables are the six soy-based endogenous variables, seven permanent shift binary variables, and a trend.

the tested variable's betas (as well as unity for the betas on the eight deterministic variables restricted to lie in the cointegration space).[15] Equation 7 is rewritten as follows:

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

In equation 10, β^c is the p1 by r (14 by 3) beta matrix with one of the variable's levels restricted to a unit vector; b is a p1 (or 14) by 1 vector with a unity value corresponding to the relevant variable whose stationarity is being tested and for the eight deterministic components restricted to the cointegration space; and φ is a p1 by (r-1) or 14 by 2 matrix of the remaining two unrestricted cointegrating vectors (Juselius 2004, p. 221). With nine deterministic components retained and the imposed rank of r=3, then equation 8's test value is distributed under the null hypothesis of stationarity as a chi-squared variable with three degrees of freedom. Evidence was sufficient to reject that four of the endogenous variables were stationary (QBEANS, PBEANS, QOIL, and, POIL), and insufficient to reject the hypothesis that QMEAL and PMEAL were stationary.[16] Evidence thereby suggests that the modeled vector of six soy-based endogenous variables is comprised of four nonstationary or I(1) and two stationary or I(0) variables in logged levels. In our case where r=3 and two variables are stationary: the two stationary variables each accounts for a separate cointegrating vector, and one cointegrating vector is a stationary combination of individually I(1) variables (Juselius 2004, pp. 221-222).

Tests of Beta Exclusions

The number of variables in the cointegration space of equation 2 is p1 = 14. The 14 exclusion tests examine whether each of these variables have zero coefficients in the three cointegrating relations. Failure to reject the null that a variable's betas are zero-valued suggests that the variable should be excluded from the cointegration space. The hypothesis test value in equation 7 would include a 14 by 3 β-vector; a 14 by 13 design matrix, H, with 13 being the number of unrestricted beta coefficients in each relation; and a 13 by 3 matrix φ of 13 unrestricted coefficients in each of the three cointegrating relationships (Juselius 2004, chapter 10).[17] Evidence at the five percent significance level was sufficient to reject the null hypothesis of zero-valued betas for the following nine variables: QBEANS, PBEANS, QMEAL, PMEAL, URUGUAY, HIDEMAND, MADCOW, FAIRACT, and SPIKE95.[18] Evidence at the

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[15] This test can be conducted in CATS2 (beta version) in two settings: with and without inclusion of the eight deterministic variables restricted to the cointegration space: NAFTA, URUGUAY, FAIRACT, NEWFBILL, HIDEMAND, MADCOW, SPIKE95, and TREND. We chose to include these eight deterministic variables in the tests , due to the institutional importance of events for which the variables were defined.

[16] Given a rank of 3, the test values and parenthetical p-values are as follows, with the null of stationarity rejected for p-values less than 0.05: 11.6 (0.01) for QBEANS, 10.8 (0.01) for PBEANS, 18.1 (0.000) for QOIL, 14.5 (0.002) for POIL, 5.83 (0.12) for QMEAL, and 5.6 (0.13) for PMEAL.

[17] Basically, the φ matrix is the β-matrix without the beta coefficients for the variable being tested for exclusion.

[18] The exclusion test values (and parenthetical p-values) for these nine variables were as follows: 50.7 (0.000) for QBEANS; 10.4 (0.02) for PBEANS; 38.2 (0.000) for QMEAL; 15.0 (0.002) for PMEAL; 12.8 (0.01) for URUGUAY; 8.9 (0.03) for HIDEMAND; 17.0 (0.001) for SPIKE95; 7.6 (0.06) for FAIRACT; and 7.5 (p= 0.06) for MADCOW. The results for the FAIRACT and MADCOW binary variables were marginal, as the test values reflected evidence that was insufficient to reject the null of zero-valued coefficients at the 5-percent level, but not at the very marginal 6 percent level. Previous research uncovered evidence that the 1996 farm bill and the December 2003 discovery of bovine spongiform encelopathy (BSE or "mad cow" disease) in Washington State suggested that both events were important in explaining the workings of these same U.S. soy-based markets (BBRS 2004, pp. 29-30; Vendatum 2004; Milling and Baking News 2004, p. 20). Given the marginal evidence of the exclusion tests for the FAIRACT and MADCOW binary variables, as well as the cited additional evidence on the important roles that

five percent level was insufficient to reject the null hypothesis that each of the following five variables had zero-valued beta coefficients: QOIL, POIL, NAFTA, NEWFBILL, and TREND.[19] The latter five variables' beta coefficients were restricted to zero.

Set of Sequential Hypothesis Tests on Individual Beta Coefficients

When the model is estimated with stationary data, one must identify the long run structure of the three cointegrating relations which emerged as equations 4, 5, and 6 after having imposed the chosen rank of three, the five statistically supported exclusion restrictions, and the two statistically supported stationarity conditions (on QMEAL and PMEAL). Under the rank condition of identification, one identifies the three relations by imposing at least r-1 or 2 restrictions on each of these cointegrating relations (Juselius 2004, pp. 245-246).

One generally chooses testable restrictions on equations 4-6 that have been restricted for the two stationarity conditions and the five variable exclusion restrictions just discussed. These added testable hypotheses arise from theory, market knowledge, suggestions implied by coefficients generated by equations 4-6, and/or are required to meet the rank condition of identification (Juselius 2004, pp. 245-246). The test value in equation 7 is used with equation 8 (Juselius 2004, pp. 245-246). Those which evidence fails to reject are retained, and the Johansen-Juselius reduced rank estimator[20] is applied to re-estimate the three cointegrating relations with the last-accepted and statistically supported restriction(s) imposed. One repeats this process sequentially to obtain a set of finally-restricted cointegrating relationships. Restrictions are accepted for "high" p-values above 0.05 (corresponding throughout to a five-percent level of statistical significance). Table 4 summarizes the sequential hypothesis test results.

Test set 1 (table 4) provides the first set of restrictions of the sequential hypothesis test process. [Throughout, CV1 – CV3 refer to the three cointegrating vectors or relationships.] This set identified all three equations and included the five exclusion and two stationarity conditions supported statistically above, as well as three normalizations.[21] This entailed 7 restrictions on the first cointegrating relation or vector (CV1), and eight restrictions on each of the CV2 and CV3 relations. In order to meet the rank condition of identification, we set β(QMEAL) and β(PMEAL) to zero on CV1, a relation normalized on QBEANS. We chose these two identifying restrictions because recent econometric research on these same markets suggested that QMEAL and PMEAL were minor contributors to QBEANS' forecast error variance, and appeared logical and appropriate zero restrictions in order to identify CV1.[22] The test set 1's hypothesis value was 44.8 (17 degrees of freedom or df) with a p-value of 0.000, which rejected the restrictions. We clearly must continue searching for more restrictions to add to test set 1 to generate a fully restricted cointegration space that is statistically supported.

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the 1996 U.S. Farm Bill and BSE discovery in the Washington State have played in U.S. soy-based markets, we opted to consider total evidence as insufficient to exclude MADCOW and FAIRACT from the cointegration space.

[19] The exclusion test values (and parenthetical p-values) for these nine variables were as follows: 5.3 (0.15) for QOIL, 6.0 (0.11) for POIL, 1.5 (0.69) for NAFTA, 1.6 (0.66) for NEWFBILL, and 3.7 (0.30) for TREND. In these five cases, evidence was soundly insufficient to reject the null hypothesis of zero-valued beta coefficients.

[20] This reduced-rank estimator is summarized in Johansen (1988), Johansen and Juselius (1990, 1992), and Juselius (2004, chapters 8-10). We do not summarize this well-known reduced rank estimator here.

[21] The three chosen normalizations were on QBEANS, the first cointegrating vector (CV1); on QMEAL for CV2, and on QMEAL for CV3.

[22] See Babula, Bessler, Reeder, and Somwaru 's (2004, pp. 46-50) detailed analyses of decompositions of forecast error variance on the same monthly U.S. system of three soy-based product markets.

Table 4
Sets of Sequential Hypothesis Tests on Specific Beta Estimates or Beta Estimate Subsets

Tested Restrictions, restriction numbers in each cointegrating vector (CV)	**Explanation/Reasons**	**Test value, parenthetical p-value, results.**
Test set 1: Testing 5 exclusion, 2 stationarity, and various identifying conditions		
<u>7 in CV1</u>: β(QOIL) = β(POIL) =β(NAFTA) =β(TREND)=β(NEWFBILL)=0; β(QMEAL) = β(PMEAL) = 0	5 zero or exclusion restrictions. 2 identifying restrictions.	Chi-square value = 44.8 (df=17) with p-value of 0.000. As p-value is less than 0.05, reject the restrictions. More restriction inquiry and tests needed.
<u>8 in CV2</u>: β(QBEANS)=β(PBEANS)= β(PMEAL)=β(QOIL)=β(POIL) = 0; β(NAFTA)=β(NEWFBILL)=β(TREND)=0	Needed for QMEAL stationarity. Zero restrictions on permanent shifters from exclusion tests.	
<u>8 in CV3</u>: β(QBEANS)=β(PBEANS)= β(QMEAL)=β(QOIL)=β((POIL)=0; β(NAFTA)= (NEWFBILL)=β(TREND)=0	Needed for QMEAL stationarity; Zero restrictions from exclusion tests.	
Test set 2: previous test set 1's restrictions plus: β(FAIRACT)=0 imposed on CV1 and β(POIL) =0 relaxed in CV1		
<u>7 in CV1</u>: test set 1's 7 restrictions carried over: plus β(FAIRACT) = 0 less β(POIL) =0	Analysis, previous estimations' results; BBRS(2004) analysis and market expertise suggests POIL important	Chi-squared test value =44.7 (df=17) had slight improvement (decrease) from previous estimation. But p-value of 0.003 suggests evidence rejects rest set 2's restrictions. More restriction inquiry and tests needed.
<u>8 in CV2</u>: test set 1's 8 restrictions retained.		
<u>8 in CV3:</u> test set 1's 8 restrictions retained.		
Test set 3: previous test set 2's restrictions less β(NEWFBILL) = 0 relaxed in all 3 CVs.		
<u>6 in CV1</u>: test set 2's 7 restrictions retained: less β(NEWFBILL) = 0 that is relaxed.	.	Chi-squared test value = 53.6 (df=14) generated a p-value of 0.000 that rejected the restrictions. There were various non-reported improvements in CV coefficient t-values that led to our retention of test set 3's restrictions and conclusion that we need more restriction inquiry and tests.
<u>7 in CV2</u>: test set 2's 8 restrictions rretained less β(NEWFBILL) = 0 that is relaxed.		
<u>7 in CV3:</u> test set 2's 8 restrictions retained: less β(NEWFBILL) = 0 that is relaxed.		
Test set 4: previous test set 3's restrictions plus β(URUGUAY) = 0 in CV1.		
<u>7 in CV1</u>: test set 3's 6 restrictions retained: plus β(URUGUAY) = 0.	Insignificant β in CV1, previous estimation.	Chi-squared value of 32.7 (df=15) improves (declines) and generates a p-value which rejects the restrictions at the 5% level, but accepts them at the 1% level. More restriction inquiry and tests needed.
<u>7 in CV2</u>: test set 3's 8 restrictions rretained.		
<u>7 in CV3:</u> test set 3's 8 restrictions retained.		
Test set 5: previous test set 4's restrictions plus β(NEWFBILL)=β(MADCOW)=0 in CV1.		
<u>9 in CV1</u>: test set 4's 7 restrictions retained: plus β(NEWFBILL)=β(MADCOW) = 0.	Insignificant βs in CV1, previous estimation	Chi-squared test value improves(falls) to 32.2 (df=17) and generates p-value =0.02. Evidence rejects at 5% but accepts at weaker 2% level. More restriction inquiry and tests needed.
<u>7 in CV2</u>: test set 4's 7 restrictions rretained.		
<u>7 in CV3:</u> test set 4's 7 restrictions retained.		

Table 4
Sets Sequential Hypothesis Tests on Specific Beta Estimates or Beta Estimate Subsets (continued)

Tested Restrictions, restriction numbers in each cointegrating vector (CV)	**Explanation/Reasons**	**Test value, parenthetical p-value, results.**
Test set 6: previous test set 5's restrictions plus β(HIDEMAND) = 0 in CV2.		
9 in CV1: test set 5's 9 restrictions retained. 8 in CV2: test set 5's 7 restrictions rretained: plus β(HIDEMAND) = 0 . 7 in CV3: test set 5's 7 restrictions retained.	Insignificant β in CV2, previous estimation.	Chi-square value of 34.2 (df=18) generates a p-value of 0.01 which again rejects the restrictions at the 5% level, but accepts them at the 1% level. More restriction inquiry and tests needed.
Test set 7: previous test set 6's restrictions plus β(FAIRACT) = 0 in CV3.		
9 in CV1: test set 6's 9 restrictions retained. 8 in CV2: test set 6's 8 restrictions rretained. 8 in CV3: test set 5's 7 restrictions retained: plus β(FAIRACT) = 0	Insignificant β in CV3, previous estimation.	Chi-square test value of 34.4 (df=19) generated a p-value of 2 percent, suggesting evidence that rejects restrictions at 5%., but accepts them at 2%. More restriction inquiry and tests needed.
Test set 8: previous test set 7's restrictions plus β(MADCOW) = 0 in CV3.		
9 in CV1: test set 7's 9 restrictions retained. 8 in CV2: test set 7's 8 restrictions rretained: plus β(HIDEMAND) = 0 . 9 in CV3: test set 7's 8 restrictions retained: plus β(MADCOW) = 0	Insignificant β in CV3, previous estimation	Chi-square value of 36 (df =20) retains p-value of 0.02 from last estimation. Evidence rejects restrictions at 5% level but accepts them at 2% level. More restriction inquiry and tests needed.
Test set 9: previous test set 8's restrictions less two relaxations of β(TREND) ≠0 in CV2 and β(MADCOW)≠0 in CV3.		
9 in CV1: test set 8's 9 restrictions retained. 7 in CV2: test set 8's 8 restrictions rretained: less β(TREND) = 0. 8 in CV3: test set 8's 8 restrictions retained: less β(MADCOW) = 0.	See analysis of BBRS (2004). See analysis of BBRS (2004).	Chi-square test value of 24.3 (df=18) makes market improvement from last estimation and declines. The value's p-value of 0.14 soundly exceeds the 5% level and evidence accepts the restrictions soundly. But β(NEWFBILL) in CV2 and β(MADCOW) in CV3 are insignificant.
Test set 10: previous test set 8's restrictions plus two restrictions, β(NEWFBILL) in CV2 and β(MADCOW) in CV3 .		
9 in CV1: test set 9's 9 restrictions retained. 8 in CV2: test set 9's 7 restrictions rretained: plus β(TREND) = 0. 9 in CV3: test set 9's 8 restrictions retained: plus β(NEWFBILL) = 0.	Insignificant β in CV2, previous estimation. Insignificant β in CV3, previous estimation.	Chi-square value of 25.7 (df=20) generates p-value of 0.17, suggesting strong evidence in support of test set 10's restrictions that are the finally restricted cointegrating relations.

Source: Analyses, estimations, and hypothesis test results conducted by Commission staff.

The second iteration is summarized in test set 2's restrictions: again, seven restrictions on CV1, 8 on CV2, and 8 on CV3. Test set 2 differs from test set 1 in two ways: set 2 imposes the restriction β(FAIRACT)= 0 in CV1 due to an insignificant t-value when the system was estimated with test set 1's restrictions, while β(POIL) = 0 is relaxed. Previous research suggests that POIL is important to QBEANS, CV1's left-side variable (BBRS 2004, pp. 45-49). While test set 2s' test value of 44.7 rejects the restrictions, the p-value rose slightly from test set 1's test value. This suggests some progress towards achieving a statistically accepted set of restrictions.

Test set 3 relaxes the exclusion restriction that β(NEWFBILL) = 0 in all three cointegrating relations, in addition to the already-accepted conditions in test set 2. The test value of 53.6 (df=14) generated a p-value of less than 0.05, suggesting that evidence still does not accept the restrictions and more work needs to be done in crafting a better-defined cointegration space. However, most β[NEWFBILL] coefficients are statistically significant.[23] Also, the POIL beta t-value rises markedly from the last estimation to 1.9. Given these beta results, we retain the restrictions and seek out more.

Test set 4 imposes β[URUGUAY] = 0 on CV1 because of a statistically insignificant t-value (-0.21) from the previous estimation with test set 3's restrictions, in addition to the restrictions of test set 3. This added zero restriction on the URUGUAY’s β in CV1 seems to render a restriction set the sample accepts. The test value of 32.7 (df = 15) generated a p-value of 0.052 that accepts test set 4's restrictions at the 5-percent significance levels. This latest estimation generated statistically insignificant coefficients on MADCOW (-1.21) and NEWFBILL (0.96) in CV1, which are set to zero, and that, with test set 4's conditions, renders test set 5.

Test set 5 combines test set 4's restrictions with the two CV1 restrictions that were suggested because of insignificant t-values during the last estimation: β(MADCOW) = β(NEWFBILL) = 0. The test value of 32.2 (df = 17) generated a p-value of 0.02 suggesting acceptance of the restrictions but a lower significance level of one-percent rather than five percent. Nonetheless, improved and strong patterns of statistical significance emerged for all four (non-normalized) variables remaining in CV1 as seen from the following t-values: β(PBEANS), t-value = -11.4; β(POIL), t-value = -3.6; β(HIDEMAND) , t = -5.1; and β(SPIKE95), t = -4.6. All CV1 right-side coefficients are strongly significant, and effort is placed on testing for and imposing emergent restrictions on the remaining two cointegrating relations to achieve an overall acceptable basket of error correction space restrictions. The most obvious test that emerges from this estimation with test set 5's restrictions imposed is a zero restriction on β(HIDEMAND) in CV2 due to the insignificant t-value of -0.96. This restriction is added to test set 5's restrictions to render test set 6 in table 4.

Test set 6 combines test set 5's restrictions with a new CV2 restriction that β(HIDEMAND) = 0 as just mentioned. The 34.2 test value (df = 18) generated a p-value of 0.01, although evidence at the five percent level was still sufficient to reject the restrictions, implying a need for more statistical inquiry. The second CV2 seems reasonable, with all coefficients having generated a significant t-value. However, β(FAIRACT) in CV3 generated a t-value of 0.42, which suggests that the restriction of the coefficient being zero in CV2 should be added to the restriction set. Test set 7 is test set 6 plus β(FAIRACT) = 0 in CV3, and the 34.4 test value reflects acceptance at the 2- percent, level. However, β(MADCOW) generated a t-value of -1.53 suggesting that the restriction of β(MADCOW) = 0 should be added to test set 7 to form test set 8 in table 4.

Test set 8 adds β(MADCOW) = 0 in CV3 to test set 7's restrictions. The test value of 36 generated a p-value of 2 percent suggesting acceptance at a low of a significance level. However, perusal of the data plots and results from previous research suggest that perhaps two restrictions in CV2 should be relaxed: relaxing β(TREND) = 0 as trend may be present for QMEAL, the normalized CV2 variable, and relaxing β(MADCOW) = 0 for PMEAL, CV3's normalized variable (BBRS 2004).

Test set 9 is test set 8 less two restrictions that are relaxed: β(TREND) = 0 in CV2 and β(MADCOW) = 0 in CV3. Clearly, this reduced set of restrictions enhances evidence of acceptance, with the test value of 24.3 having generated a p-value of 0.14, far above the decision rule level of 0.05. Evidence accepts the test set 9 restrictions. However, this estimation generated two beta coefficients

[23] The newly unrestricted β[NEWFBILL] coefficients generated t-values of -2.7 and -3.9 in CV1 and CV2 that are significant at the 5 percent level, and a t-value in CV3 of -1.7 that is significant at the 10 percent level.

which are not significant, and whose values should perhaps be restricted to zero: β(NEWFBILL) =0 in CV2 because of a t-value of -0.46 and β(MADCOW)=0 in CV3 because of a t-value of -1.3. These two zero restrictions are added to test set 9 to render test set 10 in table 4. A test value of 25.7 (p-value of 0.17) strongly accepts the test set 10 restrictions.

Hypothesis Tests on the Adjustment Speed or α Coefficients.

We conducted hypothesis tests for exogeneity of the six endogenous soy-based variables. In effect, such a test examines whether each variable's α coefficients in the r=3 cointegrating relations are zero. If evidence suggests that a variable's α coefficients are zero in the three cointegrating relations, while some of the variable's beta coefficients are statistically nonzero, then one considers the variable as weakly exogenous (Juselius 2004, pp. 231-232). A weakly exogenous variable influences the error correcting processes through non-zero beta coefficients, but does not itself adjust to the error correction process (Juselius 2004, pp. 231-232). In equation 9, and given that r=3 and p=6: the α- matrix is a 6 by 3 matrix of adjustment speed matrix with a row of zeros for the variable being tested for weak exogeneity; A is a 6 by 5 design matrix (with 5 being the number of nonzero alphas in each of the three columns of alphas); and ψ is a 5 by 3 matrix of nonzero alphas (see Juselius 2004, pp. 231-231). Basically, the ψ matrix is the alpha matrix without the α's that are being tested as zero. The test value in equation 8 is distributed as a chi-square distribution with 3 degrees of freedom (three single alpha coefficients being zero-restricted). Evidence in all cases was sufficient to reject the null hypothesis of weak exogeneity.[24]

Economic Analysis of the Three Cointegrating Relationships for the U.S. Soy-Based Markets

The three fully identified and restricted cointegrating relationships are in equations 11, 12, and 13, which are followed by the adjustment speed (α) coefficients. Parenthetical values below the β- and α-coefficients are t-values. Clearly these estimates display notable formidable statistical strength.

$$\text{(11) QBEANS} = \underset{(-13.1)}{-0.90}\text{*PBEANS} + \underset{(+3.5)}{0.16}\text{*POIL} + \underset{(+3.5)}{0.27}\text{*HIDEMAND} + \underset{(+4.8)}{0.22}\text{*SPIKE95}$$

$$\text{(12) QMEAL} = \underset{(+3.8)}{+0.10}\text{*URUGUAY} + \underset{(+6.4)}{0.05}\text{*FAIRACT} - \underset{(-3.9)}{0.07}\text{*MADCOW} - \underset{(-6.1)}{0.07}\text{*SPIKE95}$$

$$\text{(13) PMEAL} = \underset{(-5.3)}{-0.20}\text{*URUGUAY} - \underset{(-3.5)}{0.24}\text{*NEWFBILL} + \underset{(+5.4)}{0.60}\text{*HIDEMAND} + \underset{(+5.7)}{0.44}\text{*SPIKE95} + \underset{(+7.0)}{0.001}\text{*TREND}$$

[24] The weak exogeneity test values and (parenthetical) p-values were as follows: 51.5 (0.000) for QBEANS; 8.8 (0.03) for PBEANS, 24.7 (0.000) for QMEAL, 13.5 (0.004) for PMEAL, 15.2 (0.002) for POIL, and 6.3 (0.099) for QOIL. Evidence was sufficient at 5 percent or less to reject the null of zero-valued α coefficients for all endogenous variables except QOIL. Evidence was sufficient at a significant level just below 10 percent to reject the null hypothesis of QOIL's weak exogeneity. Given the analysis of BBRS (2004), and the effects that non-soy oil has on market-clearing quantity of soy oil, we decided to treat QOIL as fully endogenous, although at a slightly lower confidence level than the other five variables. BBRS (2004) suggested that of the three markets, soy oil is the most influenced by non-soy markets due to soy oil's substitution in uses with other vegetable oils.

ALPHA

	Alpha1	Alpha2	Alpha3
△QBEANS	-0.7016	-0.5071	0.3476
	(-8.3080)	(-2.5745)	(6.2544)
△PBEANS	-0.1101	0.3565	0.0178
	(-2.4944)	(3.4643)	(0.6140)
△QMEAL	0.0039	-0.4958	-0.0041
	(0.1087)	(-5.9777)	(-0.1768)
△PMEAL	-0.1002	0.2082	-0.0684
	(-1.6554)	(1.4750)	(-1.7185)
△QOIL	0.0794	0.0603	-0.0517
	(2.2770)	(0.7415)	(-2.2523)
△POIL	-0.1585	0.5851	0.0870
	(-2.5910)	(4.1007)	(2.1619)

Of the three relations, equations (12) and (13) are attributed to the stationary variables of QMEAL and PMEAL, respectively. Equation 11 is a stationary linear combination of individually nonstationary endogenous variables, and has substantial economic interest as a demand function for soybeans. As well, the coefficients generated by the permanent shift binary variables in all three CVs provide economically interesting interpretations. The β coefficients on the endogenous variables were generated by a model formulated in natural logarithms, and may be taken as long run elasticities of response (Johansen and Juselius 1990, 1992; Juselius 2004, chapter 5). The error-correction coefficients in equations 11 through 13 reflect a set of strongly significant long run response relationships.

An Economy-Wide U.S. Demand for Soybeans.

The first cointegrating relationship appears to be a demand for soybeans. Own-price or PBEANS generated a negative and highly significant coefficient in equation 11. As well, having normalized equation 11 on soybeans quantity conceptually places QBEANS in positive form above the equilibrium on the relation's left side, whereby the adjustment coefficient corresponding to QBEANS in the first relation (column) above is negative (-0.702), very significant (t = -8.31), and suggestive of a demand's downward adjustment towards long run equilibrium (following Juselius 2004, towards the "attractor set"). The highly significant PBEANS or own-price coefficient (t-value = -13) of -0.90 suggests a long-run own-price elasticity of demand that approaches unity. Given that the error correction space illuminates equilibrium relationships in the long run, presumably over two or more soybean harvests, it is not surprising that this elasticity approaches unity. As expected, a rise in the price of soy oil would augment the demand for soy beans, with each percentage rise in POIL inducing, on average historically, a 0.16 percentage rise in QBEANS. The two periods of enhanced world oilseed demands rendered a rise in QBEANS demand, as suggested by the positive and strongly significant coefficients in equation 11 on HIDEMAND and SPIKE95.

Analysis of Deterministic Error Correction Components.

Trend appears to be unimportant, with zero-restrictions on β(TREND) statistically supported for the first two cointegrating relationships, and with a statistically significant but very small β(TREND) value of 0.001 supported for the third cointegrating relationship. Demand side influences seemed to dominate supply-side influences during the 2003:09-21004:09 period for which the HIDEMAND binary variable was defined: β(HIDEMAND) is positive and significant in both the CV1 normalized on QBEANS and CV3 normalized on PMEAL. HIDEMAND's coefficient was a highly significant 0.25 for CV1 normalized on QBEANS, and a highly significant 0.60 on CV3 normalized on PMEAL. Although BBRS (2004) cited anecdotal evidence to the contrary immediately after the December 2003 BSE discovery in Washington State, the discovery appears to have had minor effects on the soybean market. Evidence supported MADCOW's inclusion in only the second CV normalized on QMEAL, and while significant, the coefficient of -0.07 is modestly valued. This value suggests that market-clearing quantities of meal may have been diverted to feed through stock depletion, although the coefficient's -0.07 value indicates a near-zero influence.

SPIKE95 was defined for the May 1995:05 – 1997:08 period to account for the influences of the higher prices and demand levels for oilseeds worldwide. SPIKE95 generated a significant and positive coefficient on PMEAL in equation 13, and a negative, significant, but modestly valued coefficient on QMEAL in equation 12. These SPIKE95 coefficients suggest dominating demand conditions for soy products, with increases in both QBEANS and the price of its end product (PMEAL).

Directed Graphs and Innovation Accounting Analysis

We summarize dynamic soy product relationships through an analysis of forecast error variance (FEV) decompositions. We manipulated the parameters of the estimated error correction mechanism to obtain the levels VAR equivalent of the fully-restricted cointegrated VEC model (hereafter, the VEC-equivalent levels VAR).[25] We then analyzed the FEV decompositions from this VEC-equivalent levels VAR to summarize the dynamic relations among the endogenous soy-based variables.

Incorporation of information embedded in contemporaneously correlated errors or innovations is crucial to valid analysis of FEV decompositions (Sims, 1980; Swanson and Granger, 1997; Bessler, Yang, and Wongcharupan 2002, p. 811). Following Bessler, Yang, and Wongcharupan (2002, pp. 811-812), we followed a "Bernanke (1986) ordering factorization" that requires writing the innovation vector, say **e(t)**, from the estimated error correction model as : **Ae(t)** = **v(t)**,where **A** is a 6 by 6 matrix and **v(t)** is a 6 by 1 vector of orthogonal shocks. It was once common in VAR-type analysis to rely on a Choleski factorization, so that the **A** matrix is lower-triangular to achieve a just-identified system in contemporaneous time. We apply the TETRAD-II directed graph algorithm (described below). A directed graph is an assignment of causal flow (or lack thereof) among a set of endogenous variables (vertices) based on observed unconditional correlation and conditional (or partial) correlations (see Bessler and Akleman 1998).

The application of directed acyclic graphs or DAGs involves the theoretical work of Pearl (1995) and the TETRAD-II algorithms in Spirtes, Glymour, and Scheines (2000). Following Bessler and Akleman (1998), we use TETRAD-II to construct a DAG on innovations from the VEC-derived levels VAR that incorporates the statistically supported and imposed rank and hypothesis test restrictions summarized in tables 2 and 4. The algorithm is a set of commands that begins with a set of relationships among variables (innovations from each VAR equation) and proceeds step-wise to remove edges between variables so as to direct causal flow in contemporaneous time (Bessler and Akleman 1998, p. 1145). Briefly, one begins with a complete, undirected graph that places an undirected edge between every variable in the system (every variable in set V) (Jonnala, Fuller and Bessler 2002, p. 115; Bessler, Yang, and Wongcharupan 2002, p. 811-812). Edges between variables are removed sequentially on the bases of statistically zero correlations or conditional correlations (Bessler, Yang and Wongcharupan 2002, p. 812; Jonnala, Fuller, and Bessler 2002, p. 113; and Bessler and Akleman 1998, p. 1145). These conditioning variable(s) comprise the notion of a "sepset" that is, in turn, utilized to assign the direction of causal flow between variables that remain connected after all possible conditional correlations have been passed as nonzero (Bessler, Yang, and Woncharupan 2002, p. 812; Bessler and Alkeman 1998, pp. 1144-1146).

[25] Note that this is the algebraic equivalent of the finally restricted cointegrated VEC obtained above, and incorporates the reduced rank restriction of r=3, all imposed restrictions on the cointegration space, and hence differs from the unrestricted levels VAR in equation 2 developed to achieve adequate statistical specification via the utilization of the sources of non-normal statistical information.

Consider variables X, Y, and Z in a variable set V; the goal is to impose a directed edge among sets of variables: X➜Y➜Z, X⬅Y⬅Z, X➜Y⬅Z, etc.[26]

DAGs order the six endogenous variables in contemporaneous time. The starting point is figure 12, the completely unrestricted or undirected graph of all possible edges between the six variables. As noted in Bessler and Akleman (1998, pp. 1145-1146), there is a two stage process for using DAGs to establish a system of contemporaneously causal orderings among the six soy-based variables. First, the TETRAD-II algorithm analyzes the unconditional correlations, eliminates the statistically zero edges, and retains the statistically nonzero ones (Scheines et. al. 1994; Spirtes, Glymour, and Scheines 2000). And second, TETRAD-II performs a similar analysis on all conditional correlations, given the first stage's retained and statistically nonzero unconditional correlations: one omits the statistically zero ones and retains the statistically nonzero ones. The edges that emerge from the two-stage TETRAD-II selection algorithm are then imposed on the matrix of contemporaneous innovations on the VEC-derived levels VAR (Bessler and Akleman 1998).

There has been a series of recent DAG applications to VAR and cointegrated VEC models of various agricultural markets, and these applications provide detailed explanations of the workings and directed edge selection process of the TETRAD-II algorithm: Bessler and Akleman (1998); Bessler, Wang, and Wongcharupan(2002); Babula, Bessler, and Payne (2004), and BBRS (2002). Such detailed explanations are therefore not provided here and readers interested in such detail are referred to this research. Figure 13 provides the edges imposed on the VEC-derived levels VAR. All directed edges in figure 13 were generated from the two-stage TETRAD-II process, except for one undirected edge between PBEANS and PMEAL. Previous DAG work on this same database found strong evidence of a directed edge of PBEANS➜PMEAL (BBRS 2004, pp. 37-39). We included this latter directed edge as part of figure 13's system of edges imposed on the VEC-derived levels VAR contemporaneous innovation matrix (Bessler and Akleman 1998).

The data strongly accept figure 13's contemporaneous causal relationships when imposed on the innovation matrix of the VEC-derived levels VAR. Doan (1996, p. 8.10) provides a likelihood ratio statistic that tests the null hypothesis that the imposed DAG-suggested causal relationships in figure 13 are consistent with or accepted by the data, and the statistic is distributed as a chi-square variable. One fails to reject the null of data acceptance for p-values above 0.05, corresponding to the 5-percent level of statistical significance. Our test statistic of 3.2 (seven degrees of freedom) generated a p-value of 0.86, that far exceeds 0.05, and thereby suggests strong evidence of the data's acceptance of the contemporaneously causal relationships suggested by TETRAD-II in figure 13.[27]

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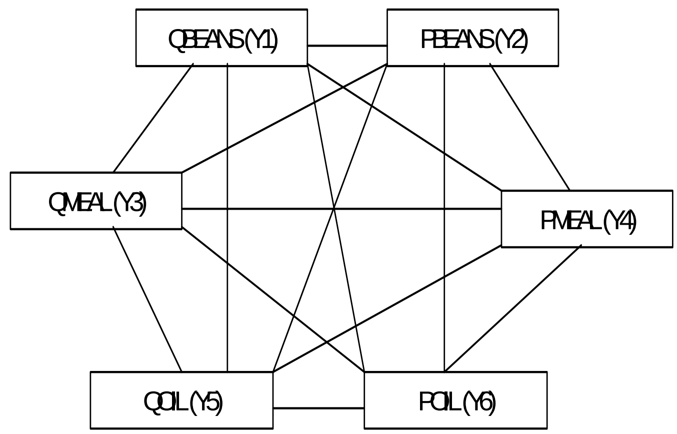
[26] Edges are directed by considering variable triples X-Y-Z, where X and Y are adjacent, as are Y and Z, but X and Z are not adjacent. Edges are directed for the triple as X➜Y⬅Z if Y is not in the sepset of X and Z (Bessler and Akleman 1998, p. 1145; Jonnala, Fuller, and Bessler 2002, p. 115). If X➜Y, Y and Z are adjacent, X and Z are not adjacent; and there is no arrow directed at Y, then one orients X–Z as Y➜Z. Should a directed path exist from X to Y and there is an edge between X and Y, then one directs X – Y as X➜Y (Bessler and Akleman 1998, p. 1145).

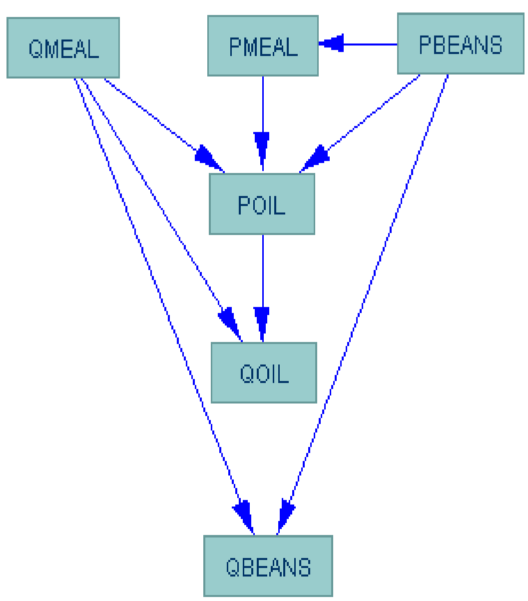
[27] We note recent research cautioning readers not to lose sight that the causal relationships implied in the directed graph of figure DAG are for *contemporaneous* time, and reflect only the relationships among the six endogenous variables at the shorter run horizons, of say six months or less (BBRS 2004, p. 39). As will be seen, a different and far richer interplay of causality patterns among the six variables emerges when the FEV decompositions, which reflect total causality, in contemporaneous time and over time as well, are examined. See BBRS (2004, p. 39).

Figure 12
Undirected graph of the six soy-based variables



Source: Commission staff analysis.

Figure 13
TETRAD-suggested directed acyclic graph on innovations from an error-correction model on U.S. soybean complex



Source: Commission staff analysis.

Analysis of Forecast Error Variance Decompositions

Analysis of forecast error variance (FEV) decompositions is a well-known accounting method for residuals or innovations, and is closely related to Granger causality analysis (Bessler 1984, p. 111; Sims 1980, 1988). While both tools provide evidence on the existence of causal relations among two variables, analysis of FEV decompositions provides well-known extensions to Granger causality tests (BBRS 2004). A modeled endogenous variable's FEV is attributed at alternative (here monthly) horizons to shocks in each endogenous variable (including itself). As a result, analysis of FEV decompositions not only provides evidence of the simple existence of a causal relationship among two variables, but it also illuminates the strength and dynamic timing of such a relationship (Saghaian, Hassan, and Reed 2002, p. 107; Bessler 1984, p. 111). Table 5 provides the FEV decompositions for the six soy-based variables. Such decompositions reflect the causal relations embedded in both the model's lag structure serially over time, as well as the DAG-suggested contemporaneous causal relationships which emerged from applying the methodologies of Bessler and Akleman (1998).

A variable is considered exogenous (endogenous) when large (small) proportions of its FEV are attributed to its own movements (that is, to own-variation). Likewise, a variable's endogeneity is suggested when large proportions of its FEV are attributed to variation in the system's other endogenous variables (Bessler 1984; Goodwin, McKenzie, and Djunaidi 2003, pp. 488-489). As well, decompositions of two or more variables may be summed at a particular horizon for a "collective" effect: for example, at a chosen horizon, the collective effect of the three soy-based prices on one of the modeled soy-based quantities can be summed and examined. Patterns of FEV decompositions are provided in table 5.

Table 5
Decompositions of Forecast Error Variance Generated by the Levels VAR Equivalent of the Fully-Restricted Cointegrated VEC with Directed Acyclic Graphs.

		Percentage of Forecast Error Variance Explained by					
Variable Explained	Monthly Horizon	QBEANS	PBEANS	QMEAL	PMEAL	QOIL	POIL
QBEANS	1	79.89	8.43	9.35	0.06	1.94	0.33
	2	75.56	8.28	12.2	1.18	1.94	0.83
	4	65.24	8.14	20.14	3.94	1.79	0.73
	6	58.19	7.50	25.26	6.53	1.85	0.68
	12	56.44	6.10	34.38	11.57	2.10	0.55
	18	45.30	5.25	39.86	14.61	2.24	0.47
	24	37.56	4.67	43.52	16.67	2.34	0.41

Table 5
Decompositions of Forecast Error Variance Generated by the Levels VAR Equivalent of the Fully-Restricted Cointegrated VEC with Directed Acyclic Graphs (continued).

		Percentage of Forecast Error Variance Explained by					
Variable Explained	Monthly Horizon	QBEANS	PBEANS	QMEAL	PMEAL	QOIL	POIL
PBEANS	1	0.38	98.08	0.24	0.03	0.43	0.85
	2	0.76	96.28	0.48	0.10	0.66	1.72
	4	1.00	94.40	0.68	0.24	0.76	2.79
	6	1.13	93.74	0.69	0.31	0.75	3.29
	12	1.21	93.22	0.67	0.37	0.72	3.78
	18	1.25	93.07	0.65	0.39	0.72	4.93
	24	1.26	93.02	0.65	0.39	0.68	4.00
QMEAL	1	1.15	2.29	94.65	0.25	1.02	0.63
	2	2.63	5.28	89.95	0.30	1.72	0.57
	4	5.55	8.99	81.73	0.59	2.71	0.44
	6	7.09	10.70	77.91	0.78	3.17	0.35
	12	9.02	12.93	73.08	1.02	3.72	0.23
	18	9.81	14.00	70.95	1.10	3.94	0.19
	24	10.25	14.70	69.69	1.14	4.06	0.16
PMEAL	1	0.71	67.48	0.01	30.07	1.63	0.11
	2	1.11	70.16	0.60	25.37	2.69	0.07
	4	1.95	71.95	1.20	21.45	3.41	0.04
	6	2.35	72.56	1.50	19.89	3.66	0.04
	12	2.71	73.25	1.75	18.39	3.86	0.04
QOIL	1	0.10	0.96	19.49	0.31	76.79	2.36
	2	1.16	0.66	22.17	0.21	73.74	2.07
	4	2.24	0.50	26.11	0.12	69.37	1.67
	6	2.66	0.48	27.59	0.08	67.68	1.52
	12	3.09	0.46	29.18	0.04	65.89	1.33
	18	3.26	0.44	29.73	0.03	65.27	1.27
	24	3.35	0.42	29.99	0.03	64.97	1.24

Table 5
Decompositions of Forecast Error Variance Generated by the Levels VAR Equivalent of the Fully-Restricted Cointegrated VEC with Directed Acyclic Graphs (continued).

		Percentage of Forecast Error Variance Explained by					
Variable Explained	Monthly Horizon	QBEANS	PBEANS	QMEAL	PMEAL	QOIL	POIL
POIL	1	0.21	45.22	1.64	9.22	0.12	43.58
	2	0.19	40.85	1.95	10.23	0.28	46.51
	4	0.11	35.46	3.13	11.03	0.63	49.63
	6	0.12	32.99	4.03	11.24	0.85	50.78
	12	0.13	30.53	5.10	11.32	1.08	51.87
	18	0.13	29.69	5.49	11.28	1.16	52.24
	24	0.13	29.27	5.74	11.21	1.21	52.43

The quantity of soybeans is noticeably exogenous at horizons of four months or less when from 65 percent to 80 percent of its behavior is attributed to own-variation. Thereafter, own-variation accounts for decreasing proportions of QBEANS' forecast error variance or FEV, that falls to 38 percent by the 24-month horizon. Soybeans quantity appears particularly influenced by the soy meal market. Meal market effects on QBEANS are particularly noticeable as horizons extend to 6 months and longer – beyond the influences of a single annual crop. At horizons of six months or more, soy bean planting decisions in the northern and southern production sectors, with harvests at approximately opposing dates in a calendar year, appear to affect the worldwide supply of soybeans. After the six month horizon, annual U.S. soybean supply or QBEANS is potentially influenced by new production (particularly from Brazil and Argentina), and the proportions of QBEANS variation collectively attributed to the soy meal market variables in table 5 rise from 32 percent to 60 percent by month-24. As expected, the price and quantity of meal crushed from QBEANS has an important influence on the quantity of soy beans.

As expected, soybean price appears highly exogenous. Among the demand and supply factors, PBEANS behavior may be particularly influenced by the available quantity of soybeans, that in turn, is largely determined by climate, especially at horizons of six months and less. PBEANS may further be exogenized by the effects of the U.S. Department of Agriculture's (USDA's) price support program using a loan rate instrument.

Soy meal quantity is relatively more exogenous at short run horizons (4-6 months or less) than at the longer horizons. From 82 percent to 95 percent of QMEAL's variation is attributed to own-variation, and own-variation's contributions ultimately fall to 70 percent by the 24-month horizon. At horizons beyond four months, the collective influence of the soybean market variables ultimately reaches 25 percent. Clearly, and as expected, the market-clearing quantity and price of soybeans have an effect on the quantities of soybeans that are crushed into soy meal.

Soy meal price is highly endogenous at all reported horizons, with as little as 18 percent and no more than 30 percent of the PMEAL variation attributed to own-variation. Soybean price heavily influences soy meal price and explains from about 67 percent to 73 percent of PMEAL's variation at all reported horizons.

Soy oil quantity is rather exogenous with from 65 percent to 77 percent of its FEV attributed to own variation. As expected with co-products, QOIL is also heavily associated with variation in its co-product, QMEAL, the variation of which explains up to 30 percent of QOIL's FEV.

It is not surprising that POIL behavior appears collectively driven by own-variation and PBEANS movements. Of soy oil price's variation, from 44 percent to 52 percent is attributed to own-variation; from 29 percent to 45 percent is attributed to PBEANS variation; and a more minor proportion, up to about 11 percent, is explained by PMEAL movements.

Overall, the FEV decomposition patterns suggest that there is a heavy causal interaction between the soybeans and soy meal markets. At horizons of six months or less comprising the window of influence of a single crop cycle, from 25 percent to 44 percent of QBEANS variation is explained by the available quantity of soy meal clearing the market, and QMEAL and PMEAL collectively account from 32 percent to 60 percent of QBEANS variation. So the market-clearing price and quantity of soy meal heavily influences the quantity of soy beans for market.

The meal market is, in turn, heavily influenced by movements in the soybean market. Most noticeably, no less than 67.5 percent of PMEAL's variation is attributed to PBEANS movements. QMEAL appears influenced by the soybean market's movements with up to 25 percent of its FEV explained collectively by movements in QBEANS and PBEANS. So QBEANS' behavior is heavily influenced by PMEAL and QMEAL variation, while the soybean market heavily affects the soy meal market, particularly through movements in PBEANS.

Causal interplay among the soy oil market and the remaining two markets is largely one-way, from the soybeans and soy meal markets to the soy oil market: the soy oil market has little to contribute to explaining the table 5 FEV decompositions for the soy meal and soybean markets. That the soy oil market affects the soybean and soy meal markets to a lesser extent than these latter two markets influence the soy oil market is not surprising for two reasons. First, soy oil accounts for only about 18 percent and soy meal accounts for over 76 percent of the volume of a 60-pound bushel of soybeans.[28] And second, while soybean oil is a leading vegetable oil in the world, it accounts for less than a fifth of world production of all "fats and oils" (combined vegetable oils, and all animal fats including tallow, fish oil, butter, and lard).[29] Moreover, substitution among vegetables and most animal fats is high and prices are generally highly correlated (Gould, Box, Perali 1991). Such a high degree of soy oil competition for and substitution patterns among soy oil and other fats and oil products may partially explain the relatively large own-variation contributions (and hence the high degrees of exogeneity of) in table 5 to the FEV decompositions for QOIL and POIL; the high levels of own-market explanations for the soy oil market variables in table 5; and the relatively high levels of "detachment" of the oil market from influences on the soy meal and soybean markets in table 5. No less than 65 percent of QOIL's variation is self-attributed, although up to 30 percent of QOIL's FEV is explained by QMEAL movements. Aside from own-variation, POIL's behavior is importantly affected by soybeans price, that accounts for up to 45.2 percent of POIL's FEV.

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[28] From USDA Agricultural Marketing Service (204, p. 3) data, each 60 pound bushel of soybeans yielded 11.06 pounds (18.4%) of soy oil, 45.86 pounds (76.4%) of soy meal, and 3.08 pounds (5.2%) of other materials. For more discussion, see BBRS (2004, p. 45).

[29] During 2003/2004, soybean oil accounted for 32% of the world production of 100 million metric tons or mmt of major vegetable oils, while palm oil accounted for 28%, rapeseed oil for 14%, and "other" oils for 26% (USDA, FAS 2004 a, b). World soybean oil production represented 18% of the 129 mmt of major vegetable oils, animal fats, fish oil, and butter (i.e., all fats and oils) (*Oil World* 2003). See also BBRS (2004, pp. 45-46).

Conclusions

There has been a steadily increasing number of applications of a methodology that combines the cointegrated VAR methods of Johansen (1988), Johansen and Juselius (1990, 1992), and Juselius (2004) with analysis of directed acyclic graphs to agricultural economic issues, as cited above. For perhaps the first time, we have implemented such an application to a monthly system of U.S. markets for soybeans, soy meal, and soybeans.

We located monthly, 1992-2004 market year data for six U.S. soy-based variables spanning three markets: market clearing prices and quantities for soybeans, soy meal, and soy oil. A levels VAR and ultimately a fully restricted cointegrated VEC of these six variables were specified and estimated.

Following Juselius (2004), we obtained a statistically adequate levels VAR by having harnessed the information inherent in the data's non-normal behavioral attributes required for valid time series econometric regressions (Granger and Newbold 1986, pp. 1-5). The benefits of such efforts suggested in Juselius (2005,chapters 4-6) are clearly evident on perusal of table 1: evidence strongly suggests that we achieved an adequately specified statistical model.

Evidence suggested that the six soy-based variables constituted a system of four nonstationary and 2 stationary variables bound together by one stationary long run cointegrating relationship that appears to be a U.S. demand for soybeans. There appears to be a price elasticity of U.S. soybean demand of -0.90 in the very long run. This near-unity elasticity may be justified when one considers that the cointegration space parameters capture market-equilibrating relationships that extend beyond the horizon of a single crop cycle, and to horizons of perhaps two years or more, when fewer resources (even planted area) are as fixed as in shorter run horizons. There is also a cross-price elasticity of U.S. soybean demand with respect to soy oil price of 0.16. The 1995-1997 and the 2003-2004 periods of high world demand and price levels of soy products appeared to positively affect demand for U.S. soybeans.

While two of the three cointegrating relationships that emerged were stationary relationships for the price and quantity of soy meal, the coefficients on the deterministic and permanent shift binary variables provided empirical illumination of the importance (or unimportance) of various market and institutional events and policy changes. The Uruguay Round's implementation appeared to bolster the U.S. soy meal market, likely through increased production and exports. While statistically significant, QMEAL's near-zero coefficient on MADCOW, defined for the late-2003 discovery of mad cow disease in the United States, failed to support BBRS's (2004) conjectures, made shortly after the discovery, that the BSE discovery would appreciably increase the demand for QMEAL as feed ingredient. The periods of high soy product demand during the 1990's and during 2003-2004 suggested demand-driven forces that resulted in both higher soy meal prices and increased depletion in soy meal stocks, supporting previous research's analysis (BBRS 2004).

Analysis of the model's decompositions of forecast error variance (FEV) illuminate further the modeled system's patterns of dynamic interactions. Soybeans price and quantity are clearly the dominant forces in explaining behavior in the other two soy product markets, as expected with "derivative" markets which are driven by the price and quantity of a commodity. There is a rich, bi-directional causal interplay among U.S. soybean and soy meal markets. But the interplay between the soy oil market and either of the other two markets is decidedly unidirectional. While QMEAL explains QOIL behavior and PBEANS noticeably explains POIL behavior, soy oil market's variables (QOIL, POIL) negligibly explain behavior in the other two markets. These results support BBRS' (2004, pp. 47-50) findings, and their explanation that the U.S. soy oil market's significantly interfaces with and intensely competes in markets for other edible oils (e.g. canola and palm oils).

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