No. ID-09

OFFICE OF INDUSTRIES WORKING PAPER
U.S. International Trade Commission

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May 2004

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ABSTRACT: This paper demonstrates the application of a recently developed methodology, the combination of directed acyclic graphs (DAGs) with Bernanke structural vector autoregression (VAR) models, to model a system of U.S. commodity-related and value-added markets. As an example, the paper applies this methodology to a monthly system of three U.S. soy-based markets: the soybean market upstream and the two downstream markets for soy meal soy oil. Analyses of results from simulating the model's impulse response function and of forecast error variance decompositions provide updated estimates of market elasticity parameters that drive these markets, and updated policy-relevant information on how these monthly markets run and dynamically interact. Results suggest how a positive shock in U.S. soy meal price dynamically influences the soybean market upstream and the soy oil market further downstream.

Results suggest that movements in commodity-based markets strongly influence each other, with many of these effects occurring in the long run beyond a single crop cycle.

Key words: Directed acyclic graphs, Bernanke structural VAR models, monthly soy-based markets.

Introduction

Prices of soy meal and of soy meal's prime ingredient, soybeans, have been escalating and are currently at record high levels not seen since the 1970s. Since the brief "grain/oilseed crisis" of high prices and low supplies during 1994-1996, world grain and oilseed markets have been mostly quiet with low and declining prices. However, in the 2003/2004 marketing year, price volatility returned swiftly, primarily because of three powerful influences: unfavorable weather, plant disease that stunted 2002 and 2003 crops in both the Northern and Southern hemispheres, and the ever-escalating Chinese grain and oilseed demands for use as raw materials. Another significant, but often overlooked, factor in 2002/2003 was the emergence of several serious livestock diseases that paralyzed production or trade in meat or related meat byproducts. Both grain and oilseed markets have been affected, with price volatility particularly pronounced in the oilseed market.[1]

We have three purposes. First is methodological: we apply new and advanced methods of directed acyclic graphs (hereinafter, DAGs) to a monthly Bernanke structural vector autoregression (VAR) model of the U.S. soybean market and of related soy meal and soy oil markets downstream (hereinafter, DAG/Bernanke VAR methods).[2] This may be the first application of these new and advanced DAG/Bernanke VAR methods to U.S. soy-related markets. Second, we estimate a monthly VAR model of the U.S. soybean, soy meal, and soy oil markets; apply DAG methods to the VAR model innovations; and then generate a series of well-known VAR econometric results that illuminate dynamic interrelationships among these markets. And third, these dynamic results are then used to characterize the effects on the three U.S. soy-related markets from the recent high soy meal prices. Such high soy meal prices are characterized by simulating the DAG/Bernanke VAR model under a shock (increase) in soy meal price.

Recent Trends in Soybeans Products

The 2003/04[3] U.S. oilseed market is perhaps at its tightest state since the 1970's when escalating grain and oilseed demands of China and the (then) Soviet Union fueled a grain and oilseed "boom." During the last several years (including 2003/04), buoyant world soybean demand, particularly from China, has reduced commercial soybean stocks and supported soy-based prices (particularly for soy meal and its main input, soybeans) at record high levels, despite a 28 percent rise in foreign (primarily Brazilian and Argentine) production during 2003/04 (USDA, World Agricultural Outlook Board 2004, p. 26). Chinese imports of 23 million metric tons (mt) in 2003/04 account for about a third of world totals, and are up sharply from 10 million mt in 2001/02 and 21 million mt in 2002/03 (USDA, Foreign Agricultural Service or FAS 2004a, table 5).

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[1] For example, USDA has projected that U.S. farm price of soybeans in 2003/2004 will rise 37 percent to $7.60 a bushel from the 2002/2003 price; corn prices will rise respectively by six percent, and wheat prices will fall by six percent. See USDA, Office of the Chief Economist.

[2] As presented below in great detail, evidence and analysis clearly demonstrates that the system of soy-based variables modeled here are stationary in logged levels, such that estimation as a VAR in logged levels is appropriate, and that cointegration is not relevant, and that estimation with the vector error correction model methods of Johansen and Juselius (1990, 1992) is unnecessary.

[3] Throughout, 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.

Among livestock diseases has been bovine spongiform encelopathy (BSE or "mad cow disease"). BSE's December 2003 discovery in Washington State led to a decrease in the use of ruminant meat and bone meal in feeds and a rise in soy meal's use as a feed ingredient.[4] In a 1997 response to a European outbreak of BSE, the U.S. Food and Drug Administration (FDA) banned the use of ruminant meat and bone meal in ruminant feeds; excluded the use of ruminant blood meal from this ban; and permitted continued use of ruminant meat and blood in non-ruminant products such as poultry and hog feeds. On January 26, 2004, shortly after the U.S. discovery of BSE, the FDA extended its ban on ruminant feed ingredients in two ways: the exemption on the use of ruminant blood meal in ruminant feeds was abolished and a ban was implemented on the use of poultry litter in ruminant feed (Vendantam 2004, p. A3; *Milling and Baking News* staff 2004, p. 20). As a result, prices of ruminant meat, bone, and blood meals plummeted from $295 per ton prior the BSE discovery to only $140 per ton by January 28 (Gullickson 2004b, p. 20; 2004b, p. 25).

Some speculate that the FDA may further extend the above-noted bans and eliminate feeding of ruminant meat and bone meal and other rendered products from the meat packing industry entirely, under the contention that it is excessively risky to keep any ruminant meat and bone ingredients in the mixed feed industry (*Oil World* staff 2004, p. 2; M. Pressler 2004, p. F1; McNeil and Grady 2004; A. Weintraub 2004, p. 39; E. Schlosser 2004; and Reuters 2004). Such a ban extension appears to have begun eliciting a demand shift from ruminant ingredients towards soy meal ingredients in feeds and in turn augment related soy meal and soybean prices – a shift which may continue.

As a result of BSE's discovery in Washington State and the historically high levels of current world import demand for soybeans, prices of soy meal and its primary input, soybeans, have been escalating (and are likely to continue doing so), with important implications for the U.S. soy-based markets for soybeans, soy meal, and soy oil. More specifically, U.S. soy-based prices rose markedly over the October 2003-March 2004 period: by 34 percent to $301 per short ton for soy meal and by 46 percent to $9.56 per bushel for soybeans (U.S. Department of Agriculture, Economic Research Service or USDA, ERS 2004a, tables 8, 10).

U.S. Vector Autoregression Model of Three Soy-Based Markets: Specification Data, Estimation, and Model Adequacy

We apply Bessler and Akleman's (1998) methodological combination of DAG-based results on causal orderings in contemporaneous time with Bernanke's (1986) structural VAR methods to form a DAG/Bernanke VAR model. We first specify a traditional VAR of six monthly soy-related variables (hereinafter denoted as the "first-stage VAR"). Bessler and Akleman's (1998) procedures are applied to the first-stage VAR of the following six U.S. endogenous soy-based variables (denoted throughout interchangeably by the parenthetical, upper-cased labels):

[4] Ruminants are animals which have hoofs, even toes, and/or horns. Ruminants include bovine animals (e.g. cattle and dairy cows), sheep, goats, and deer, among others. Ruminants carry BSE and consumption of BSE-infected ruminant meat has triggered outbreaks of BSE's deadly human counterpart, Creutzfeld-Jakop disease, in humans. Cattle and dairy herds comprise U.S. agriculture's primary ruminant herds. See Gruen (2000).

1. Market-clearing quantity of soybeans (QBEANS)
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).

Theory and recent commodity-based time-series research suggests that the three U.S. soy-related markets (soybeans upstream and for soy meal and soy oil downstream) influence each other (Babula and Rich 2001, p. 1; Babula, Bessler and Payne, pp. 1-2). We apply the new DAG/Bernanke VAR methods to illuminate just how, with what monthly dynamic patterns, and to what ultimate degrees, that such interrelationships take place.

We focus on how shocks in PMEAL influence the remaining endogenous variables in the modeled soy-related markets. Conventional theoretically-based or "structural" econometric models are equipped to address questions at static equilibria before and after an imposed shock, although they often have little to say about what happens dynamically between pre- and post-shock equilibria (Sims 1980; Bessler 1984, pp. 110-111). VAR econometric methods are well-equipped to address policy-relevant dynamic issues of what unfolds between, as well as at, pre- and post-shock equilibria while imposing a few as a priori theoretical restrictions as possible to permit the regularities in the data to reveal themselves (Bessler 1984, pp. 110-111). Such regularities provide the following dynamic aspects on how a positive shock (increase) in soy meal price can affect the remaining five respondent variables of the three soy-based markets: direction of monthly responses, magnitude of a respondent variable's ultimate change, monthly patterns which the responses of the variables take, and the strength of relationships among the six U.S. soy-based variables.

Specification Issues

The system was estimated as a VAR model in logged levels because unit root test evidence, as shown below, suggests that all six variables are likely stationary in logged levels. Detailed derivations and summaries of VAR econometric methods are provided by Sims (1980), Bessler (1984), Hamilton (1994, ch. 11) and Patterson (2000, ch. 14) and are not provided here. Tiao and Box's (1978) lag selection procedure suggested a seven-order lag structure. Consequently, the six-equation, first-stage VAR model is specified as follows:

$$
\begin{aligned}
(1)\quad X(t) = {} & a_o + a_{x,1}*QBEANS(t\text{-}1) + \ldots + a_{x,7}*QBEANS(t\text{-}7) \\
& + a_{x,8}*PBEANS(t\text{-}1) + \ldots + a_{x,14}*PBEANS(t\text{-}7) \\
& + a_{x,15}*QMEAL(t\text{-}1) + \ldots + a_{x,21}*QMEAL(t\text{-}7) \\
& + a_{x,22}*PMEAL(t\text{-}1) + \ldots + a_{x,28}*PMEAL(t\text{-}7) \\
& + a_{x,29}*QOIL(t\text{-}1) + \ldots\ldots + a_{x,35}*QOIL(t\text{-}7) \\
& + a_{x,36}*POIL(t\text{-}1) + \ldots\ldots + a_{x,42}*POIL(t\text{-}7) + \epsilon_{xt}
\end{aligned}
$$

Above, the parenthetical terms denote a value's time period: t for the current period and (t-1) through (t-7) for the seven lags. The a-terms are regression coefficient estimates. The nought-subscripted a-term refers to the intercept. Of the two subscripts on the other a-coefficients, x refers to the x-th equation, while the numeric subscript refers to the 42 lagged variables (seven lags on each of six endogenously modeled variables). X(t) = QBEANS(t), PBEANS(t), QMEAL(t), PMEAL(t), QOIL(t), and POIL(t). The term ϵ_{xt} denotes the white noise residuals' current period-t value for the x-th equation.

Each of the six VAR equations contains a time trend and a set of 11 monthly seasonal binaries (see Babula Babula, Bessler, and Payne 2004). Five relevant event-specific binary variables were defined in each VAR equation: 1994 implementation of the North American Free Trade Agreement (NAFTA); the 1995 implementation of the Uruguay Round Agreement; the 1993/1994 crop year yield reductions from severe flooding of key U.S. soybean-producing areas; the 1994/95 and 1995/96 market years of extraordinarily favorable weather; and the implementation of the 1996 farm bill (see Babula, Bessler, and Payne 2004; Babula and Rich 2001).

Since data is published in a variety of units (short tons, hundred weight, bushels), we converted all price and quantity data to a metric ton equivalent. The United States Department of Agriculture, Economic Research Service (USDA, ERS 1993-2004b) provided and/or published all data before our conversions to metric tons.

There is an unfortunate break in the monthly U.S. soybean, soy oil, and soy meal market data during calendar year 1991, when USDA, ERS (1993-2004b) discontinued reporting on a monthly basis and reported instead on a quarterly basis. However, USDA, ERS (1993-2004b) resumed monthly reporting during 1992, and continues to present. As a result, there is a "break" in the monthly data before and after calendar year 1991, such that econometric estimation with monthly data further back than 1992 is not possible. This left the data available for the market years 1992/93 through part of 2002/2003. Given this "break" in the monthly time series data in 1991, the crop/market years for soy-based products which begin in September or October, and the seven-order lag structure suggested by Tiao and Box's lag selection methods applied here, the monthly estimation period emerged: 1993:05 through 2003:07, and it can be considered a small sample estimation.

Following recent VAR econometric research on commodity-based markets, quantities were defined as market-clearing quantities that are a sum of a month's beginning stocks, production, and imports for soy meal and soy oil (Babula, Bessler, and Payne 2004, p. 6; Babula and Rich 2001, p. 4). Because monthly soybean production data are not available, the market-clearing soybean quantity was equivalently defined as a monthly sum of exports, volumes crushed, and ending stocks.

The first-stage VAR model was appropriately estimated with ordinary least squares (OLS) since evidence (presented below) suggested that data were stationary in such form (Sims 1980; Bessler 1984). Following recent research, the estimations were done in logged levels so that shocks to, and impulse responses in, the logged variables provided approximate proportional changes in the non-logged variables (Goodwin, McKenzie, and Djunaidi 2003, p. 484; Babula, Bessler, and Payne 2004, p. 5).

Hamilton (1994, pp. 324-327) noted that a VAR model may be considered a reduced-form of a structural econometric system. And as a result, modeled quantities are not those specifically supplied or demanded, while modeled prices are not those at which quantities are specifically supplied or demanded. Rather, modeled reduced-form quantities and prices are those that clear the market (Hamilton 1994, pp. 324-327; Babula and Rich 2001, p. 5; Babula, Bessler, and Payne 2004, p. 5). Any simulation's shock-induced changes in a price and quantity are net changes, that is, the net overall change after the sometimes countervailing effects of supply and demand have played out (Babula and Rich 2001, p. 5; Babula, Bessler, and Payne 2004, p. 5).

Cointegration

Because evidence from a battery of unit root tests conducted on the VAR model's six endogenous variables in logged levels, on balance, suggested stationarity, cointegration was not an issue. As a result, a VAR model of the logged levels was chosen over a vector error correction (VEC) model as suggested by Johansen and Juselius (1990, 1992).

When a vector system of individually nonstationary variables moves in tandem and in a stationary manner, the variables are said to be cointegrated (Johansen and Juselius 1990, 1992). With more than two cointegrated variables, one should model the vector system as a VEC with Johansen and Juselius' (1990, 1992) maximum likelihood methods. However, evidence from a battery of unit root tests suggested that the data in logged levels were likely stationary.

Two main unit root tests were applied: the augmented Dickey-Fuller or ADF $T\mu$ test[5] and the small-sample version of the Bayesian odds ratio test suggested by Sims (1988). Harris (1995, pp. 27-29) and Kwiatowski, Phillips, Schmidt, and Shin (1992) discuss the well known Dickey Fuller (or DF) type test limitations of generating false conclusions of nonstationarity particularly when, as in this study, samples are finite and when variables are stationary but have near-unity roots, that is are "almost nonstationary." In such cases, DF-type unit root tests often fail to reject the null hypothesis of nonstationarity. Accepted procedure in such cases has been to treat the variables as stationary without differencing them (Harris 1995, pp. 27-29; Kwiatowski et. al.1992; Babula, Bessler, and Payne 2004, p. 6; and Babula and Rich 2001, p. 7). Following recent research, we supplemented the evidence from the ADF and Bayesian unit root tests with results from a test developed by Kwiatowski et. al. (hereinafter the KPSS test). When evidence from the ADF and Bayesian tests suggested that evidence was sufficient to reject its null hypothesis of nonstationarity, we concluded that the variable was likely stationary.[6] On the other hand, when primary tests suggested ambiguous results, a third test, that of KPSS test was employed to "break the tie"[7] (see Babula and Rich 2001, pp. 6-7). The three quantity variables in the VAR (QBEANS, QMEAL, QOIL) generated evidence in both the ADF and Bayesian tests that was sufficient at the five percent level to reject the null hypothesis of nonstationarity, leading to our conclusion that these variables be treated as stationary variables.[8] The three VAR prices (PBEANS, PMEAL, POIL) generated ADF test evidence which suggested nonstationarity and Bayesian test evidence which suggested

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[5] For details on the Dickey-Fuller and augmented Dickey-Fuller tests, see Fuller (1976), Dickey and Fuller (1979), and test procedure summaries in Hamilton (1994) and Patterson (2000).

[6] The ADF $T\mu$ tests the null hypothesis of nonstationarity, which is rejected when the pseudo-t statistic is negative and has an absolute value exceeding that of -2.89 at the 5% level and that of -2.58 at the 10% significance level (Hamilton 1994, p. 763). The Bayesian odds ratio tests the null hypothesis of nonstationarity, which is rejected when the test value algebraically exceeds the critical value for small sample tests (see Doan 1996, p. 6.21).

[7] Kwiatowski, Phillips, Schmidt, and Shin (Kwiatowski et. al. (1994) discuss the well-known DF-type test problems of generating false conclusions of nonstationarity when, as in this study, samples are small and variables have a near-unity root. They noted that classical hypothesis testing usually requires strong sample evidence to reject a null hypothesis (nonstationarity in each of the ADF and Bayesian tests employed). In such cases, Kwiatowski et. al. developed a test, the "KPSS test," with a null hypothesis of stationarity (rather than nonstationarity as with the other two employed unit root tests) for use as supplemental evidence when evidence was ambiguous concerning the existence of a unit root. One rejects the null hypothesis of stationarity when the KPSS test value exceeds the critical value at the chosen significance level (here 5 percent).

[8] Evidence at the 5% significance level was sufficient to reject the ADF $T\mu$ null hypothesis of nonstationarity because the following three test values were negative and had absolute values greater than that of the -2.89 critical value: -5.6 for QBEANS, -4.5 for QMEAL, and -3.0 for QOIL. Bayesian odds ratio test evidence was sufficient to reject the null hypothesis of nonstationarity because the following values algebraically exceeded the parenthetical critical values for cases of small samples: 21.8 (-0.5) for QBEANS, 12.8 (-0.02) for QMEAL, and 1.3 (0.43) for QOIL.

stationarity, such that net indications were ambiguous on whether the three prices were each stationary.[9] As suggested in recent literature, we used the KPSS test to "break the tie" on unit root evidence for the three prices (Babula and Rich 2001; Babula, Bessler, and Payne 2004). In all cases, evidence was insufficient to reject the KPSS null hypothesis of stationarity, leading to the conclusion that all three prices are stationary.[10]

In summary, then, we treated all six soy-based VAR variables as stationary in logged levels because two tests out of three generated evidence which suggested stationarity. As a result, we modeled the six variables as a VAR model in logged levels, precluding the relevance of cointegration and precluding the need to model the system using Johansen and Juselius' (1990, 1992) VEC methods.

Adequacy of the First-Stage VAR Model's Specification: Diagnostic Evidence

The VAR model was appropriately estimated with ordinary least squares (OLS) using Doan's (1996) RATS software over the period of May 1993 through July 2003 because of previously cited data issues. Following recent time-series econometric research, the model was judged as adequately specified based on evidence from Ljung-Box portmanteau and Dickey Fuller or DF $T\mu$ tests on the residual estimates of the six VAR equations.

The Ljung-Box portmanteau ("Q") statistic tests the null hypothesis that the equation has been adequately specified, with the null being rejected for high Q-values (Granger and Newbold 1986, pp. 99-101). For the following five equations, Ljung-Box Q values ranged from 28.1 to 44.5, fell below the critical chi-squared value of 50.89 (36 degrees of freedom), suggested that evidence at the one-percent significance level was insufficient to reject the null hypothesis of model adequacy, and led to the conclusion that the equations are adequately specified: QBEANS, QMEAL, PMEAL, QOIL, POIL. However, with a Q-value of 52.0, which exceeds the critical Q-value of 50.89, evidence at the one-percent significance level was sufficient to reject the hypothesis that PBEANS was adequately specified, although the PBEANS Q-value approached the critical value.

Granger and Newbold (1986, pp. 99-101) caution against exclusive reliance on Ljung-Box pormanteau tests for assessing evidence of adequate model specification. Consequently, we followed recent VAR econometric research and employed DF $T\mu$ stationarity tests on the VAR equations' estimated residuals as supplemental evidence of specification adequacy, with stationary (nonstationary) residuals suggesting adequacy (inadequacy) of model specification (see Babula, Bessler, and Payne 2004, p. 7; Babula and Rich 2001, p. 7). With Dickey-Fuller $T\mu$ test values ranging from -10.7 to -12.6, and critical values of -2.89 (5% level) and -3.51 (1% level), evidence is strongly sufficient at either the one-

[9] The following three ADF $T\mu$ values were negative but had absolute values below that of the critical value of -2.89, such that evidence in all cases was insufficient to reject the null hypothesis that each variable was nonstationary: -2.20 for PBEANS, -2.0 for PMEAL, and -2.2 for POIL. Insofar as the following Bayesian unit root test values algebraically exceeded the parenthetical critical values for small samples, evidence was sufficient to reject the null in each case that the variable was nonstationary: 1.70 (+0.23) for PBEANS, 2.90 (-0.32) for PMEAL, and 1.80 (+0.22) for POIL. Evidence is ambiguous for the three prices: the ADF tests suggest nonstatonarity and the Bayesian tests suggest stationarity.

[10] Evidence generated by all three prices was insufficient at the 1% significance level to reject the null hypothesis of stationarity because the following KPSS test values were less than the critical value of 0.216: 0.182 for PBEANS, 0.117 for PMEAL, and 0.156 for POIL. Consequently, we concluded that KPSS evidence suggested that all three prices were stationary. See Kwiatowski et. al. (1992).

or five-percent levels to reject the hypothesis of nonstationarity for all six VAR equations and to conclude that DF evidence suggests stationarity for all six variables.

Based on combined Ljung-Box and DF test evidence, we concluded that all six variables are likely adequately specified. Despite near-marginal Ljung-Box evidence of inadequate specification, we concluded that evidence on balance suggested that the PBEANS equation was adequately specified because the DF $T\mu$ value of -11.2 so strongly suggested that the equation's residuals were well behaved.

Time-variance of estimated regression parameters (that is, "statistical structural change") is a potential problem. Existence of structural change generally signifies that market relationships embedded in the regression coefficients have changed such that the regression coefficients vary over time (that is, there is time-variance of coefficients), and that the coefficients estimated over the entire period are invalid (Babula and Rich 2001, p. 8; Babula, Bessler, and Payne 2004, p. 7). Existence of structural change often requires division of the sample into subsamples at the juncture of the changes' occurrence and re-estimation of the model over each of the subperiods (Babula and Rich 2001, p. 8). If patterns of change were not adequate to induce structural change and time-variance of coefficient estimates, then one may validly estimate over the entire sample period and proceed as if the coefficients are time-invariant. Following established econometric research procedure, we applied a two-tiered structural change test that combines CUSUM/CUSUM-squared and Chow test procedures (Babula and Rich, p. 8).[11] Evidence from the two-tiered test did not suggest structural change for the six VAR equations.

Directed Acyclic Graph (DAG) Analysis and Formulation of a DAG/Bernanke VAR

Having specified and estimated a first-stage VAR of the six soy-based endogenous variables, we now transform this VAR into a DAG/Bernanke structural VAR using Bessler and Akleman's (1998) procedures. The first-stage VAR above makes thorough use of lagged causal relationships (serially causal relationships) among QBEANS, PBEANS, QMEAL, PMEAL, QOIL, and POIL. These soy-based variables are clearly correlated in contemporaneous time as well, although the first-stage VAR methods do little or nothing to address such contemporaneous correlation (Bessler 1984, p. 114). It is well known that ignoring a VAR's contemporaneous correlations (or orderings) among variables may render impulse response simulations and FEV decompositions that are not representative of observed market relationships (Sims 1980; Bessler 1984, p. 114; and Saghaian, Hassan, and Reed 2002, p. 104).

Traditionally, VAR econometric work has accounted for contemporaneous correlation in three principal ways. First is the Choleski factorization, the most frequently applied method, where contemporaneous correlations are established through imposition of a theoretically-based and recursive causal ordering on the VAR's variance/covariance matrix (Bessler 1984, p. 114; Bessler and Akleman 1998, p. 1144; Babula, Bessler, and Payne 2004, p. 8). The second approach is Bernanke's (1986) structural VAR methods where prior notions of hopefully evidentially based and/or theoretically grounded contemporaneously causal orderings may be imposed on a VAR's endogenous variables (Bessler and Akleman 1998, p. 1144). Having noted that impulse response and FEV decomposition results vary with the ordering chosen for Choleski-ordered and Bernanke structural VARs, Pesaran and Shin (1998) developed a third approach: a generalized impulse response analysis for VAR models (and

[11] In the first tier, the recursive residuals for the VAR equations were generated using Doan's (1996) software and the data-analytic CUSUM/CUSUM-squared plot-test methods detailed in Harvey (1990, pp. 153-155) were applied to discern potential points or junctures of structural change. In a second tier, a Chow test for structural change should be conducted at each potential juncture of potential change suggested by the CUSUM/CUSUM-squared test plots.

for cointegration or VEC models as well) that avoids orthogonalization of shocks and that generates order-invariant results (Babula, Bessler, and Payne 2004, p. 8).

These three approaches have drawbacks summarized by Babula, Bessler, and Payne (2004, p. 8). A problem with a Choleski-based approach is that the world may not be recursive and a drawback of Bernanke's approach is that the true contemporaneous orderings assumed by the researcher may be in fact unknown. Doan (2002, p. 4) recommends caution when using Pesaran and Shin's generalized impulse analysis because of difficulty in interpreting impulses from highly correlated shocks within an orthogonalized setting. Further, Doan (2002, p. 4) notes that Pesaran and Shin's methods are equivalent to computing shocks with each shocked variable, in turn, set atop a Choleski ordering.

Following Babula, Bessler, and Payne (2004, pp. 8-9), we apply Bessler and Akleman's (1998) procedures, here to the three-market soy-based system. Bessler and Akleman (1998) combined DAG analysis procedures of Scheines et. al. (1994) in order to glean data-embedded evidence to optimally choose a set of causal relations from a set of competing systems that are theoretically plausible or sanctioned. We then impose the evidentially supported causal relations on a Bernanke-type structural VAR. These methods render evidentially based patterns of contemporaneous correlations for analysis of impulses and innovation accounting results that are reasonable given the data set (Saghaian, Hassan, and Reed 2002, p. 104). In so doing, we avoid excessive reliance on recursive restrictions, expert opinion, and arbitrariness in choosing among competing but otherwise theoretically consistent sets of contemporaneous orderings inherent in more traditional Choleski-ordered or Bernanke structural VARs.

We apply DAG methods of Bessler and Akleman (1998) to the six soy-related variables and impose the DAG-suggested lines of contemporaneous orderings (using Bernanke's VAR procedures) on our estimated first-stage VAR. The resulting DAG/Bernanke VAR that emerges then generates VAR econometric results, including parameter estimates for these markets, that illuminate the dynamic monthly relationships driving the system of soybean, soy meal, and soy oil markets. Such is accomplished by analysis of impulse response simulations and FEV decompositions that emerge from the DAG/Bernanke VAR.

Directed Graphs and the PC Algorithm[12]

The application of DAGs involves the theoretical work of Pearl (1995) and the TETRAD II algorithms developed in Sprites, Glymour, and Scheines (2000). Following Bessler and Akleman (1998) and Babula, Bessler, and Payne (2004, pp. 10-11), we use TETRAD II (Scheines et. al. 1994) to construct a DAG on innovations or residuals from the first-stage VAR of soy-based variables.

A directed graph is a picture representing the causal flow among a set of variables (Jonnala, Fuller, and Bessler 2002, p. 113). The TETRAD II algorithm begins with a set of relationships among variables (innovations from each VAR equation) and proceeds stepwise between variables, so as to direct causal flow in contemporaneous time by removing statistically zero edges and retaining statistically nonzero ones (see 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 (Jonnala, Fuller, and Bessler 2002, p. 115). Edges between variables are removed sequentially on the basis of zero correlations or zero partial (conditional) correlations (Jonnala, Fuller, and Bessler 2002, p. 113; Bessler, Wang, and

[12] This section and summary of DAG procedures relies heavily on the summaries of four published studies using DAGs: Bessler and Akleman (1998, pp. 1144-1145), Bessler, Yang, and Wongcharupan (2002, pp. 795-799); Babula, Bessler, and Payne (2004, pp. 9-11); and Jonnala, Fuller, and Bessler (2002, pp. 113-115).

Wongcharupan 2002, p. 812; Bessler and Akleman 1998, p. 1145). These conditioning variable(s) on removed edges between variables comprise Bessler and Akleman's (1998, pp. 1144-1146) "sepset" of the variables whose edge has been removed.[13]

DAG Applications to the Soy-Related Endogenous Variables

We apply DAGs to sort out how the six endogenous variables are ordered in contemporaneous time. Hereafter, the six variables are denoted interchangeably by the parenthetical Y terms: QBEANS (Y1), PBEANS (Y2), QMEAL (Y3), PMEAL (Y4), QOIL (Y5), and POIL (Y6). The starting point is panel A of figure 1, that captures the completely undirected graph of all possible edges between the seven variables. There is a two-stage, and possibly three-stage, process for using DAGs to establish a contemporaneously causal orderings among the six soy-based variables (see Babula, Bessler, and Payne (2004, p. 10)). First, the TETRAD II algorithm analyzes unconditional correlations, eliminates the statistically zero edges, and retains the statistically nonzero ones (Scheines et. al. 1994; Sprites, Glymour, and Scheines 2000). Second, the algorithm does the same sort of analysis on all remaining conditional correlations: eliminates the statistically zero ones and retains the statistically nonzero ones. Panel B in figure 1 provides the edges retained in these two stages. The choice set of possible orderings has clearly decreased from panel A's set. Were the retained panel B edges fully directed, none of which are, we would have a unique set or system of edges to be imposed on the first-stage VAR model's variance/covariance matrix (via Bernanke's structural VAR methods to render Bessler and Akleman's DAG/Bernanke VAR). But panel B provides a set of 5 undirected edges. Each of the undirected edges gives rise to two possible or observationally equivalent edges: for example, considering (QBEANS – PBEANS, Figure 1), there are the two observationally equivalent possibilities of QBEANS ➞PBEANS or QBEANS ⬅ PBEANS. In such cases where TETRAD-suggested edges are undirected, there is a third stage of analysis developed by Haigh and Bessler (2003). They modified Schwarz's (1978) loss metric; applied it to the alternative systems of causality; and then chose the system of causality that minimized the Schwarz metric (panel c of figure 1). The metric-minimizing system of relationships in panel C is imposed on the DAG/Bernanke model.

The VAR model's estimation period ranges from May, 1993 through July, 2003 (1993:05–2003:07).[14] Innovations, ϵ_{it} (t-th period value, ith equation), from the first-stage VAR outlined above, provided the contemporaneous innovation matrix, Σ. Directed graph theory explicitly points out that the off-diagonal elements of the scaled inverse of this matrix are the negatives of the partial correlation coefficients between the corresponding pair of variables, given the remaining variables in the matrix (Bessler, Yang, and Wongcharupan 2002, p. 812; Bessler and Akleman 1998, p. 1146). Under the assumption of multivariate normality, Fisher's Z-statistic may appropriately test the hypothesis of each element being statistically nonzero (Jonnala, Fuller, and Bessler 2002, p. 115; Bessler and Akleman 1998, p. 1146).

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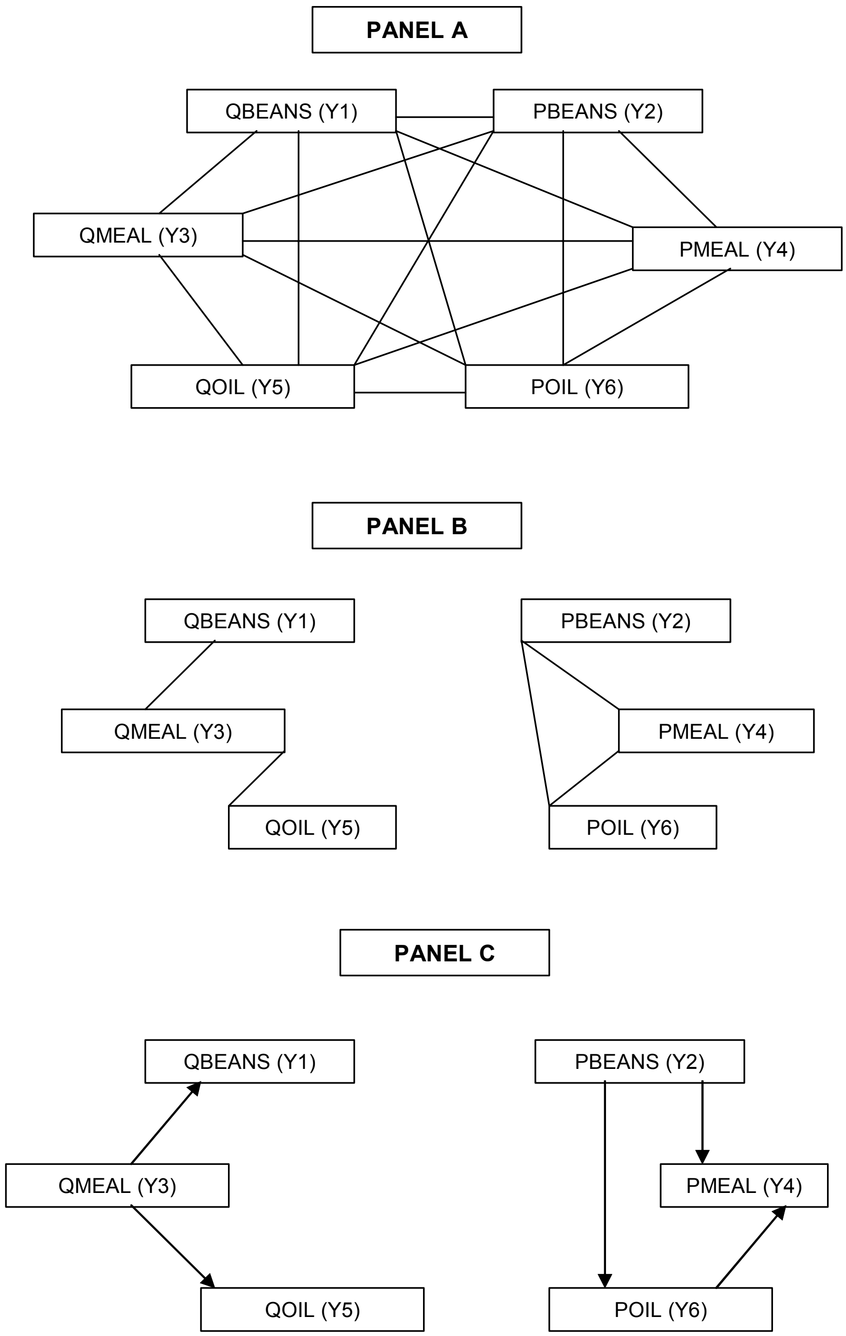
[13] Edges are directed by considering variable triples X-Y-Z, where X and Y are adjacent as are Y and Z, but X and Z are not adjacent. Edges are directed for the triple as X ➞ Y ⬅ Z if Y is not in the sepset of X and Z (Bessler and Akleman 1998, p. 1145; Jonnala, Fuller, and Bessler 2002, p. 115). If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

[14] Hereafter, monthly dates are numerically denoted with the digits right of the colon ranging from 1 through 12 to reflect January through December, respectively.

Figure 1
Complete Undirected Acyclic Graph or DAG (Panel A), TETRAD-Generated graph (Panel B) and Final DAG (Panel C) on Innovations from the First-Stage VAR Model of Soy-Related Variables



Source: Commission staff.

Table 1 contains the essentials of the TETRAD II analysis' first two stages. The correlation matrix (lower triangular innovation correlation matrix) was generated by the OLS-estimated first-stage VAR model. Each of the elements are denoted as "rho" such that rho(1,3), or its symmetric equivalent rho(3,1), denotes the correlation between variables QBEANS(Y1) and QMEAL(Y3). The p-values for these correlations are provided in the second lower triangular matrix. Following recent DAG research, we chose a 10 percent significance level (Bessler and Akleman 1998, p. 1146; Babula, Bessler, and Payne 2004, p. 10). Basically, one retains all unconditional correlations in TETRAD II's first stage and all conditional correlations in TETRAD II's second stage, with p-values of 0.10 or less (Haigh and Bessler 2003):

- QBEANS (Y1) – QMEAL (Y3): an undirected edge where soybean quantity and soy meal quantity are interrelated. Rho(3,1) equals +0.37 with a p-value of zero (rounded to the third place and far below the chosen significance level of 0.10 or 10% significance level). This edge has two observational equivalents: Y1 ➜Y3 or Y3 ➜Y1.

- PBEANS (Y2) – PMEAL (Y4): an undirected edge where soybean and soy meal prices are interrelated. Rho (4,2) equals +0.77, with a p-value of 0.00 (below 0.10). This edge's two observational equivalents are Y2 ➜Y4 and Y4 ➜Y2.

- PBEANS (Y2) – POIL (Y6): an undirected edge where soybean and soy oil prices are interrelated. Rho (6,2) equals +0.70 and has a p-value of 0.000 (below 0.10). This edge's two observational equivalents are Y2 ➜Y6 and Y6 ➜Y2.

- QMEAL (Y3) – QOIL (Y5): an undirected edge where soy meal and soy oil quantities are interrelated. Rho(5,3) equals +0.35, and has a p-value of 0.000 (below 0.10). This edge's two observational equivalents are Y3 ➜Y5 and Y5 ➜Y3.

- PMEAL (Y4) – POIL (Y6): an undirected edge where soy meal and soy oil prices are interrelated. Rho (6,4) equals +0.35 and has a p-value of 0.000 (below 0.10). This edge's two observational equivalents are Y4 ➜Y6 and Y6 ➜Y4.

Since all of these five TETRAD-suggested edges are undirected, there 32 possible (or competing) and observationally equivalent six-equation systems of contemporaneous correlations.[15] The challenge is to choose the optimal system of six equations from the 32 systems which best fits the data. Haigh and Bessler (2003) adapted Schwarz's (1978) loss metric to this problem of discerning among competing and theoretically consistent systems of contemporaneous causal relations. Since we choose among competing causality relationships in contemporaneous time, one may express contemporaneous relationships in regression form and in terms of the innovation (or residual) estimates which were generated by the six equations of the first-stage VAR model.[16] Each of the 32 systems of six causal relationships were so-expressed in regression form, estimated, and then scored by Haigh and Bessler's

[15] To conserve space, these 32 six-equation systems are not provided here, and are available by request from the authors.

[16] For example, consider that Y1 causes Y2; in contemporaneous time it can be expressed as a regression of the innovations of Y2 against those of Y1 and a constant. Likewise, Y2's causality of Y1 in contemporaneous time can be expressed as a regression of Y1's innovations against those of Y2 and a constant. As well, a variable is expressed as exogenous in contemporaneous time by regressing its innovations solely against a constant. See Haigh and Bessler (2003).

Table 1
VAR Model's Correlation and Covariance Matrices and Correlation *p*-Values in Lower-Triangular Form

QBEANS (Y1)	PBEANS (Y2)	QMEAL (Y3)	PMEAL (Y4)	QOIL (Y5)	POIL (Y6)
1.00					
0.23	1.00				
0.37	0.01	1.00			
0.18	0.77	-0.07	1.00		
0.26	0.14	0.35	0.05	1.00	
0.13	0.70	-0.08	0.35	0.08	1.00
***p*-Values for Correlations**					
0.000					
0.010	0.000				
0.000	0.895	0.000			
0.052	0.000	0.463	0.000		
0.004	0.118	0.000	0.592	0.000	
0.159	0.000	0.368	0.000	0.362	0.000

Source: Results of the TETRAD II algorithm.

(2003) adapted Schwarz loss metric.[17] We then selected the following system which minimized Haigh and Bessler's adapted Schwarz loss metric (the non-constant regressors and dependent variables refer to the first-stage VAR residuals):

(2) QBEANS = f (CONSTANT, QMEAL)
(3) PBEANS = f(CONSTANT)
(4) QMEAL = f(CONSTANT)
(5) PMEAL = f(CONSTANT, PBEANS, POIL)
(6) QOIL = f(CONSTANT, QMEAL)
(7) POIL = f(CONSTANT, PBEANS)

The innovation-based regression system (equations 2-7) is alternatively expressed diagrammatically as the DAG in panel C of figure 1, and was imposed on our VAR to form the DAG/Bernanke VAR model. Summarily, we started with a set of undirected edges (figure 1, panel A) which generated perhaps scores of competing, theoretically sanctioned systems of edges; reduced this number down to 32 competing systems of six contemporaneously correlated relationships using TETRAD II; and then applied Haigh and Bessler's adapted Schwarz (1978) loss metric to find the one system of the 32 which optimized the metric. As a result, we do not rely on arbitrary choice in choosing among the 32, otherwise theoretically

[17] Haigh and Bessler (2003) adapted Schwarz's loss metric as follows:

$$SL^* = \log(|\Sigma^*|) + k^*\log(T)/T, \text{ where}$$

Σ^* is a diagonal matrix with diagonal values of the variance/covariance matrix associated with a linear representation of the disturbance terms from an acyclic graph fit to the innovations of a VAR model.

sanctioned, systems of competing causal relationships. This method met Pesaran and Shin's (1998) recommendation of finding a method that delivers one, unique ordering.

Doan's[18] methods provide a likelihood ratio test of how well the imposed DAG-suggested contemporaneously causal relations in figure 1, panel C fit the data. With Doan's likelihood ratio test value of 18.6 falling below the critical chi square value of 23.2 (10 degrees of freedom), evidence at the 1-percent level is insufficient to reject the null hypothesis that the contemporaneous correlations that were suggested by the TETRAD II and Haigh/Bessler analyses are consistent with the data. The imposed system of orderings of the VAR variables in contemporaneous time and the sample are likely compatible.

Analysis of Impulse Responses from an Increase in Soy Meal Price

An important tool of VAR econometrics useful in applied work is the impulse response function that simulates, over time, the effects of a one-time shock in one of the system's series on the other endogenous variables in the system (Bessler 1984, p. 111; Hamilton 1994, ch. 11). This is accomplished by converting the VAR model into its moving average (MA) representation, the parameters of which are complex combinations of the VAR regression coefficients (Bessler 1984, pp. 113-114). One then imposes a one-time exogenous shock on one of the VAR variables. We chose to shock the impulse response function with an increase in PMEAL. This shock presumably arises from a BSE-induced shift towards soy meal feed ingredients and from record high levels of world import demand for soy meal's prime ingredient, soybeans. The impulse responses (hereinafter, impulses) of the respondent variables provide a map on how the soy-based markets respond to the shock (Goodwin, McKenzie, and Djunaidi 2003, p. 486). More specifically, the impulse response patterns illuminate the dynamic nature and patterns of monthly responses when one of the variables (here PMEAL) is shocked (Babula, Bessler, and Payne, p. 12). The dynamic results which emerge from the patterns of monthly impulses are (1) reaction times required for the monthly impulses to begin, (2) direction of impulses (increases or decreases), (3) pattern of monthly impulse responses, and (4) an elasticity-like multiplier of response showing the degree of ultimate respondent variable reaction.

Having estimated the DAG/Bernanke VAR in natural logarithms, shocks to, and impulse responses in, the logged VAR variables approximate proportional changes in the non-logged series (Babula, Bessler, and Payne 2004, p. 12). Using literature-established methods, multipliers are calculated from the statistically non-zero impulse responses which arose from the simulation where a rise in PMEAL was imposed on the DAG/Bernanke VAR.[19]

Such multipliers have been calculated with those impulse responses that have likely achieved a chosen level of statistical significance. Bessler, Yang, and Wongcharupan (2002, p. 819) noted that the DAG/Bernanke VAR methodology used here and Bernanke's structural VAR methods are confronted

[18] We employed Doan's (1996, p. 8.10) techniques of estimation of the contemporaneous correlation structure which emerged from the first two steps of TETRAD II analysis and the Haigh/Bessler adaptation of Schwarz's loss metric minimization.

[19] To calculate the response multipliers for a respondent variable's impulses elicited by the imposed PMEAL increase, one (1) sums the impulse responses into a cumulative proportional change in the respondent variable, (2) sums the corresponding impulses in the shock variable into a cumulative proportional change in the shock variable, and (3) then divides the respondent variable's cumulative change by the cumulative shock variable change. What results is an elasticity-like multiplier that provides what has been interpreted as history's long run average percentage change in the respondent variable per percentage point change in the shock variable. Unlike an elasticity, it is reduced form in nature and not defined for a particular point in time. These methods are summarized in Goodwin, McKenzie, and Djunaidi 2003, p. 486) and Babula, Colling and Gajewski (1994).

with a procedural shortcoming: there is not yet a widely available method of determining which of a respondent variable's impulses are statistically non-zero at a chosen significance level. Such is of crucial importance because: (1) often only a subset of a respondent variable's calculated impulses likely achieve statistical significance at levels of 10 percent or less, and (2) reliable multipliers calculated with only the statistically nonzero impulses can generate a response multiplier for the respondent variable which markedly differs from that calculated with longer streams of both significant and insignificant impulses. Software packages, such as Doan's (1996) RATS provide routines for imposing the Monte Carlo methods of Kloek and Van Dijk (1978) to discern statistical significance of impulses generated from more traditional VAR models ordered with Choleski decompositions. While calculating standard errors for impulses (to discern impulse levels of significance) generated by such Choleski-ordered models is a straightforward task, Bessler, Yang, and Wongcharupan (2002, p. 812) and Babula, Bessler, and Payne (2004, p. 12) note that such calculations for a DAG/Bernanke structure are far more challenging and beyond the scope of their studies. We follow these two studies' lead and leave the provision of such Monte Carlo methods for discerning which DAG/Bernanke VAR impulses are significant to future research. We follow recent literature-established procedures, and use simulation results from having alternatively modeled the three-market soy-based system as a Choleski-ordered VAR to aid in discerning which subset of each respondent variable's impulses generated by the DAG/Bernanke VAR simulations were relevant to the calculation of response multipliers.[20] The impulses from the respondent variables of QBEANS, PBEANS, QMEAL, QOIL, and POIL are provided in figure 2.

The PMEAL increase imposed on the DAG/Bernanke VAR was presumed to arise from such events as the U.S. discovery of BSE and from historically high and escalating world demands for soy meal's main ingredient, soybeans. Recent VAR econometric research on U.S. commodity markets established that there is some subjective leeway in identifying the source of shocks on this (or any) reduced form model (Babula, Bessler, and Payne 2004, p. 14; Babula and Rich 2001, p. 10). The PMEAL increase could have arisen from other sources: perhaps a supply-side event such as decreased production or from a change in consumer demand. However, our presumed source of the shock is valid.[21]

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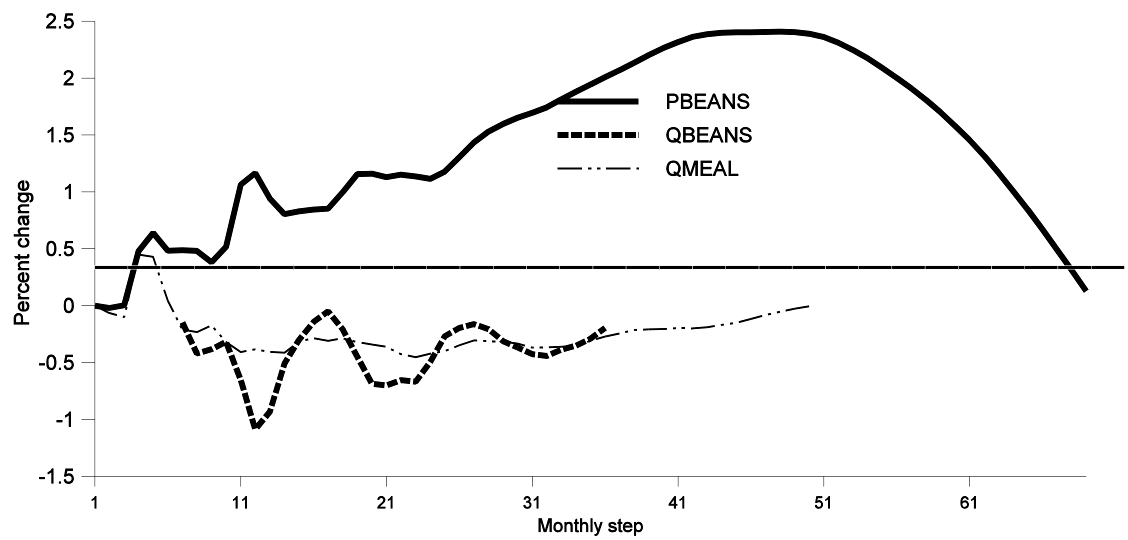
[20] We alternatively modeled our six-equation first-stage VAR model with a Choleski decomposition; applied Kloek and Van Dijk's well-known Monte Carlo methods to our simulation of a PMEAL shock (increase); and noted that in no case did monthly impulses achieve statistical significance beyond about a year. In order to be conservative and flexible, and given the differences in the degree of restrictiveness of the DAG/Bernanke and Choleski orderings, we calculated the response multipliers for the impulse responses generated for horizons through 18 months. Due to a lack of Monte Carlo methods applicable to DAG/Bernanke and Bernanke structural VARs, using related, albeit not strictly comparable, Choleski VAR simulations to discern the statistically non-zero subsets of each respondent variable's impulses with which to calculate the response multipliers followed recent literature-established procedures (see Babula, Bessler, and Payne 2004, p. 13). Any impulses comprising assumed reaction times in the response patterns were not included in the multiplier calculations provided later in the paper.

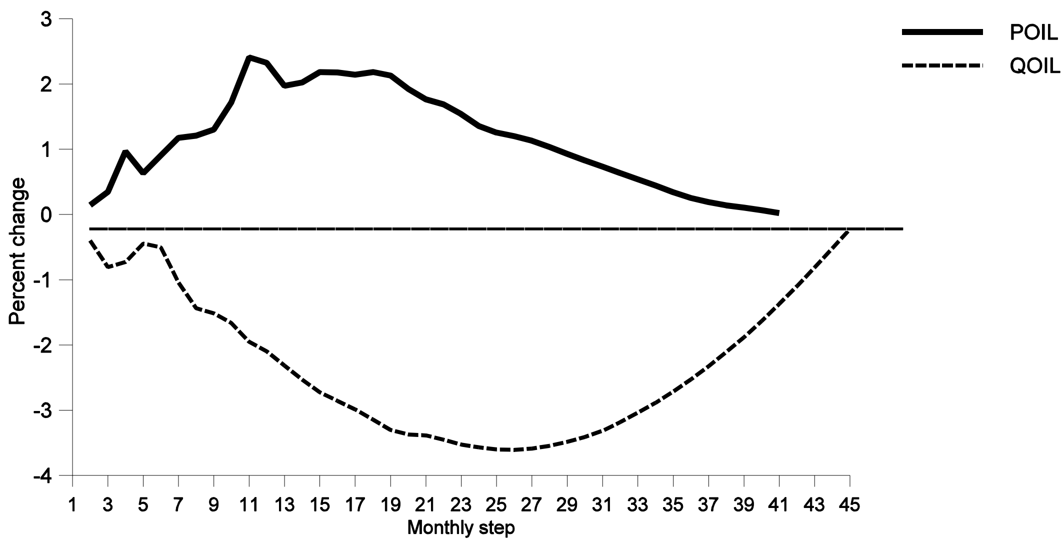
[21] For example, Babula, Bessler, and Payne (2004, pp. 10-11) estimated a similar model as this for U.S. wheat-based markets. They imposed a rise in wheat price on the model and presumed it to be tariff-induced (imported and domestic wheat consignments were shown as likely substitutable). They acknowledged that the rise in wheat price could have arisen from other sources as well: from changes in production costs or from changes in demand.

Figure 2
Monthly Impulse Responses in Soy-Based Markets to a Rise in Soy Meal Price

Panel A: Impulse responses in the soybean and soy meal markets



Panel B: Impulse responses in the soy oil market



Source: Compiled from results from econometric estimation of the DAG/Bernanke VAR model.

Table 2 and figure 2 summarize the impulse response results from imposing a one-time increase in PMEAL on the DAG/Bernanke VAR model.[22] The one-time rise in PMEAL has own-market effects which conform to theoretically based expectations. QMEAL begins responding rather immediately, that is during the same month as (within 29 days of) the imposed PMEAL increase. Throughout, such is considered as a "reaction time" of zero months.[23] The reduced-form, market-clearing soy meal quantity begins declining as QMEAL's negative demand-side elements more than overtake the positive supply-side (pro-production) effects, so as to decrease the overall quantity of soy meal which clears the market. These declines are initially pronounced, and then level-off towards zero over time. On average historically, each percentage rise in PMEAL has elicited a 0.50 percent decline in QMEAL.

Table 2
Dynamic Aspects and Multipliers of Respondent Variables from a Positive Shock in Soy Meal Price

Dynamic Aspect	Soybean Quantity (QBEANS)	Soybean Price (PBEANS)	Soy Meal Quantity (QMEAL)	Soy Meal Price (PMEAL)	Soy Oil Quantity (QOIL)	Soy Oil Price (POIL)
Reaction times (months)	6	3	0	Shocked	0	0
Response direction	Decrease	Increase	Decrease	Shocked	Decrease	Increase
Pattern of monthly responses	Cycling patterns that dampen over time	Roughly bell-shaped	Cycling patterns that dampen over time	Shocked	Bell-shaped: Accelerating then decelerating	Bell-shaped: Accelerating then decelerating
Response multiplier	-0.80	+1.70	-0.50	Shocked	-4.60	+4.0

Notes.—Response multipliers provide a percentage change in the respondent variable per percentage point change in the shock variable. Sign does not necessarily denote direction of change, but rather the relationship of the response to shock variable movements: a positively (negatively) signed multiplier signifies responses that are similarly (oppositely) directed to movements in the shock variable.

Source: Compiled by Commission staff from simulation results from the DAG/Bernanke VAR model.

Upstream effects on the U.S. soybean market of the one-time PMEAL increase, as expected, emerge as a reduced soybean quantity and a higher soy bean price that clear the market. Given the fact that soybeans are produced once annually in the northern hemisphere and six months later in the southern hemisphere, it is not surprising that evidence suggests a reaction time of about six months before any

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[22] The shock imposed was one orthogonalized innovation of 2.4 percent. However, it is well known that for such double-logged and linear VAR models, the shock size and shock sign are arbitrary. For example, the impulse response simulations of a 20 percent shock are obtained by simply multiplying the impulses from simulating a 10 percent shock by the scalar 2.0. Likewise, the impulses generated from simulating a 10 percent decline in a shock variable are obtained by simply multiplying the impulses generated from a 10 percent positive shock by the scalar -1.0. See Babula, Colling, and Gajewski (1994, p. 377).

[23] Generally, QMEAL responds, as expected, negatively to an imposed rise in own-price, PMEAL. However, at very short run horizons of six months or less, there are three positive, although negligibly valued, QMEAL impulses. QMEAL is defined as an overall market-clearing quantity. If any of these first QMEAL impulses are statistically significant, QMEAL could conceivably rise in the very short run in a number of ways: for example, a PMEAL-induced rise in imports could outweigh a decline in exports for a short term QMEAL spike upward, although this is historically unlikely. Nonetheless, it is important to note two points concerning QMEAL's impulse responses in figure 2: (1) the short term QMEAL increases are of negligible magnitude and very short lived, and (2) the preponderance of the QMEAL impulses take on a clearly defined and persistent bell-shaped pattern of declines.

PMEAL-induced effects on soybean quantity arise.[24] Once QBEANS begins declining, the monthly impulses unfold in recurring cyclical patterns that are most pronounced through about the one-year horizon, and then moderate and dampen in strength towards zero over time. On average historically, each percentage rise in PMEAL has elicited a decline of 0.80 percent in QBEANS. Given the storability of soybeans and the year-round trading on various exchanges, it is not surprising that the PBEANS has a lesser reaction time (3 months) than QBEANS in response to the shock in soy meal price. Soybean price then takes a generally upward pointing path, which ultimately levels off towards zero over time. On average historically, PBEANS rises 1.70 percent for each percentage rise in soy meal price. Given that the shock variable, PMEAL, reflects movements in a QMEAL variable which accounts for about three-fourths of soybean quantity, the supra-unity value of this multiplier seems plausible.[25]

There are some downstream effects of the PMEAL increase on the soy oil market. Generally, there are far less reaction times for PMEAL-shock-induced impulses in the soy oil market than in the meal and bean markets. As well, there are far more than proportional responses from the positive PMEAL shock in the market-clearing soy oil quantity and price than in the other two markets for two reasons. First, soy oil physically comprises a minority share of (18 percent) soybeans, which is far less than soy meal's 76 percent of soybean volume. As a result, percentage changes in soybean and soy meal market variables likely translate into noticeably larger changes in soy meal market variables.[26] And second, soy oil is highly substitutable with other oils such as rapeseed and palm oil in a wide variety of food and industrial uses. As a result, the adjustments in market-clearing soy oil quantity and price are likely augmented by adjustments in demands and supplies in these other oil markets, giving rise to rather large response multiplier magnitudes.

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[24] During the first six months, there were a number of positive and negative impulses in QBEANS. These first six QBEANS impulses were generally erratic and took no clear pattern until after the sixth impulse when a clearly defined, pronounced and projected pattern emerged. Owing to the above-mentioned lack of Monte Carlo procedures to generate standard errors of impulses to discern impulse statistical significance, we cannot determine if these first six QBEANS impulses are statistically zero or nonzero. However, we assumed that these first six impulses were statistically zero (and eliminated them from the plot in figure 2) for three reasons, based on overall evidence generated by this study, alternative models of our six variables, and theory. First, QBEANS is defined from USDA, ERS (1993-2004b) situation and outlook data to reflect reduced-form, market-clearing quantities which are likely invariant at shorter run horizons of about six months or less, insofar as soybeans comprise an annual crop grown in both the northern and the southern hemisphere which have seasons and harvests that are approximately six months apart. Second and most importantly, as seen in ensuing analysis of the FEV decompositions, PMEAL variation contributes little, even negligibly, to the explanation of QBEANS behavior at horizons of six months or less. And third, we modeled our VAR system as a Choleski-ordered VAR, simulated a positive shock in PMEAL, and generated impulse response patterns for QBEANS. We applied Kloek and VanDijk's (1978) Monte Carlo methods to the resulting Choleski VAR impulse patterns, and results suggested that (at the 5% significance level) the first six QBEAN impulses were indeed insignificant at the 5% level. Using Choleski-ordered VAR simulations to aid in determining DAG/Bernanke VAR impulse patterns of significance in the wake of a lack of Monte Carlo procedures follows recent literature using DAG/Bermanke VAR models (see Babula, Bessler, and Payne (2004, p. 13)

[25] From USDA data, each 60-pound bushel of soybeans yielded 11.06 pounds of soy oil (18.4%), 45.86 pounds of meal (76.4%), and 5.2 pounds of other materials (5.2 percent). See U.S. Department of Agriculture or USDA, Agricultural Marketing Service (2004, p. 3).

[26] As just cited above from USDA data, each 60-pound bushel of soybeans yielded 11.06 pounds of soy oil comprising less than a fifth (18.4%) of the pre-crushed volume. See U.S. Department of Agriculture, Agricultural Marketing Service. *Grain and Feed Weekly Summary and Statistics* (Feb. 27, 2004) vol. 52, no. 9, p. 3.

While the world's leading vegetable oil, soy oil only accounts for a third of world production of vegetable oil, and 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).[27] Moreover, substitution among vegetable oils and most animal fats is high, and prices highly correlated (Gould, Box, and Perali 1991).

Contrasted to soybean oil, soybean meal accounted for 70 percent of world protein meal production in 2003/2004 (USDA, FAS 2004b). Moreover, although other oilseed meals or feed grains (e.g. wheat) can be substituted for soybean meal in some animal feeds, the amount of substitution is limited by technical and functionality factors, such as maximal fiber content or protein requirements (Bickerton and Glauber 1990, pp. 9-11). Thus, there are fewer direct substitute oilseed or protein meals for soybean meal, and this is reflected in a more notable degree of price inelasticity of demand for soybean meal with regard to changes in the price of other oilseed meals (see Gardner, Roningen, and Liu, 1990).

Within a month period or so, soy oil quantity starts falling and soy oil price starts rising after an upward shock in PMEAL. Both impulse response patterns are bell-shaped. On average historically, each percentage rise in soy meal price has elicited a 4.6 percent decline in soy oil quantity and a 4.0 percent rise in soy oil price for reasons cited above.

Analysis of Forecast Error Decompositions

Analysis of forecast error variance (FEV) decompositions is a well-known accounting method for residuals or innovations (Bessler 1984, p. 111; Sims 1980). Such analysis is closely related to Granger causality analysis. 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 (Babula, Bessler, and Payne 2004, p. 15). 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 3 provides the FEV decompositions of the DAG/Bernanke VAR model of six soy-based variables. Such decompositions reflect the causal relations embedded in both the model's seven-order lag structure over time, as well as the DAG-suggested contemporaneous causal relationships which emerged from applying the methodologies of Bessler and Akleman (1998) and Haigh and Bessler (2003).

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). 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.

[27] During 2003/2004, soybean oil production accounted for 32 percent of the world production of 100 million metric tons (mmt) of major vegetable oils, while palm oil accounted for 28 percent, rapeseed oil for 14 percent, and "other" oils for 26 percent (USDA, FAS 2004b). Worldwide soybean oil production represnted 18 percent of the 129 mmt of major vegetable oils, animal fats, fish oil, and butter (all fats and oils) (*Oil World* staff 2004).

Table 3
Decompositions of Forecast Error Variance Generated by the Soy-Based DAG/Bernanke VAR

Variable Explained	Monthly Horizon	QBEANS	PBEANS	QMEAL	PMEAL	QOIL	POIL
		Percentage of Forecast Error Variance Explained by					
QBEANS	1	84.33	1.43	12.59	0.11	1.46	0.08
	2	75.40	6.18	16.12	0.11	1.33	0.87
	4	66.94	8.53	15.16	2.55	1.77	5.05
	6	61.61	9.42	17.52	2.54	3.21	5.70
	12	56.44	12.70	15.44	6.90	3.09	5.43
	18	52.46	13.41	15.53	7.19	3.57	7.83
	24	50.49	13.38	14.94	9.80	3.66	7.73
	30	49.93	13.33	14.96	10.30	3.79	7.68
	36	49.40	13.09	14.86	10.94	3.93	7.78
	48	48.83	12.89	14.08	11.48	4.03	7.96
	60	48.54	12.88	14.81	11.68	4.02	8.08
PBEANS	1	1.29	97.09	0.62	0.00	0.74	0.26
	2	0.96	96.09	2.07	0.00	0.54	0.34
	4	1.62	88.40	5.60	1.65	2.43	0.31
	6	2.66	85.15	6.61	2.42	2.54	0.61
	12	4.09	77.64	6.76	6.93	3.04	1.55
	18	3.57	73.27	5.96	11.01	4.64	1.55
	24	3.47	66.24	4.85	15.80	8.29	1.35
	30	3.72	56.32	3.94	22.06	11.92	2.05
	36	3.56	45.80	3.37	28.16	14.62	4.50
	48	2.95	29.78	3.45	38.00	15.28	10.55
	60	2.41	23.80	4.18	41.86	13.58	14.19
QMEAL	1	0.23	1.58	98.04	0.08	0.04	0.02
	2	1.51	2.21	95.38	0.25	0.21	0.43
	4	2.58	7.08	80.58	5.86	2.07	1.83
	6	3.33	12.49	71.54	5.63	4.98	2.01
	12	10.85	13.32	57.30	10.49	5.60	2.45
	18	10.06	13.51	49.35	14.04	6.84	6.20
	24	9.78	13.66	43.84	18.99	7.22	6.51
	30	9.19	12.96	40.76	21.84	7.74	7.52
	36	8.81	12.19	38.78	24.25	7.68	8.29
	48	8.69	12.38	37.53	25.02	7.47	8.90
	60	8.80	14.16	35.37	24.65	8.51	8.52
PMEAL	1	2.29	63.22	0.60	24.39	0.45	9.06
	2	2.32	63.48	0.53	21.90	0.66	11.12
	4	2.55	58.30	2.24	23.67	0.91	12.33
	6	3.18	54.64	2.50	22.46	0.99	16.24
	12	3.48	44.86	2.87	16.67	1.09	31.04
	18	3.10	42.20	2.97	15.29	1.72	34.73
	24	3.96	41.78	2.71	14.05	5.79	31.71
	30	5.30	38.03	2.10	16.62	12.64	25.31
	36	5.62	30.65	1.68	24.11	16.97	20.97
	48	4.11	18.13	2.17	38.14	17.16	20.29
	60	2.98	12.86	3.32	44.15	14.51	22.18

Table 3—*Continued*
Decompositions of Forecast Error Variance Generated by the Soy-Based DAG/Bernanke VAR

Variable Explained	Monthly Horizon	QBEANS	PBEANS	QMEAL	PMEAL	QOIL	POIL
		Percentage of Forecast Error Variance Explained by					
QOIL	1	0.27	0.18	11.54	3.45	84.29	0.28
	2	2.63	2.78	10.67	11.53	69.53	2.86
	4	4.16	5.71	11.57	11.28	64.55	2.73
	6	7.53	7.95	11.12	12.62	58.03	2.76
	12	8.25	7.41	4.65	27.41	39.97	12.31
	18	6.14	6.16	3.57	36.84	28.53	18.76
	24	4.43	4.86	3.71	42.26	22.62	22.12
	30	3.41	3.68	4.16	45.88	18.86	24.00
	36	2.94	3.50	4.74	47.20	16.48	25.14
	48	3.90	9.17	5.09	42.57	16.06	23.22
	60	5.00	15.28	3.41	39.23	19.23	17.86
POIL	1	0.45	42.10	0.90	0.07	0.10	56.38
	2	2.11	40.54	3.76	0.30	0.51	52.77
	4	6.26	41.55	3.94	1.88	3.53	42.84
	6	7.15	44.61	3.34	3.33	3.25	38.32
	12	8.13	44.34	2.55	12.82	3.66	28.49
	18	6.62	41.25	2.21	21.46	3.73	24.74
	24	6.17	39.26	2.12	25.55	3.80	23.09
	30	6.09	38.36	2.17	27.07	3.80	25.52
	36	6.17	38.19	2.21	27.28	3.78	22.37
	48	6.21	38.34	2.25	27.17	3.81	22.22
	60	6.18	38.21	2.22	27.37	3.99	22.03

Source: Compiled by Commission staff from results generated by the DAG/Bermanke VAR model.

The quantity of soybeans is highly exogenous at horizons of six months or less, when from 62 to 84 percent of its behavior is attributed to its own-variation. Beyond six months, QBEANS becomes more endogenous with more than half of its variation explained by the collective movements of the five other VAR variables. Soybean quantity appears most influenced by its own market, with moderate influences arising from downstream price and quantity movements. At horizons of 12 months and beyond, the explained proportions of QBEANS' behavior are attributed as follows: 61 to 69 percent collectively to its own market workings (PBEANS and QBEANS), and from 25 to 33 percent collectively to all three prices (PBEANS, PMEAL, and POIL).

Soybean price appears exogenous at horizons of 18 months or less when no less than 73 percent of PBEANS' variation is self-attributed. PBEANS rapidly takes on an increasingly endogenous role as time progresses: after horizons of 18 months, own-variation's explanation of soybean price's behavior drops to low as 24 percent. QBEANS' direct explanation of soybean price seems minimal at all reported horizons. However, PBEANS appears <u>indirectly</u> influenced by soybeans quantity through the collective workings of the two downstream markets for soybeans' products of meal and oil, which in turn are affected by movements in upstream movements in the soybean market. At horizons beyond 18 months, the proportions of PBEANS' FEV attributed to the workings of the soy meal market reach a collective 46 percent (PMEAL and QMEAL), proportions of FEV attributed to the collective workings of the soy oil market reach 28 percent (POIL and QOIL), and proportions of FEV collectively attributed to the workings of both downstream markets reach more than 70 percent. However, movements in the three modeled quantities have a modest effect on PBEANS and collectively explain no more than 22 percent of PBEANS' variation at the reported horizons. Therefore, the U.S. soybeans market at the farm gate appears primarily driven by movements in largely exogenous PBEANS and QBEANS, as well as noticeably by movements in the downstream markets for soybeans' two co-products.

Soy meal quantity is exogenous at short run horizons of six months or less, when from 72 to 98 percent of its behavior is attributed to its own-variation. As horizons lengthen beyond six months, QMEAL behavior is decreasingly explained by own-variation, and increasingly explained by own-price (PMEAL). Prices heavily influence QMEAL behavior at horizons of 12 months or more: own price explains up to 25 percent, while the three modeled soy-based prices collectively explain up to 47 percent of QMEAL's variation. QBEANS and QOIL variation have modest influence on soy meal quantity, with neither explaining more than about 11 percent of QMEAL variation at horizons of 12 months or beyond. QMEAL appears more influenced by movements in price than by quantity movements.

Soy meal price is endogenous at all reported horizons: own-variation accounts for as little as 14 percent and for no more than 44 percent of its behavior at all reported horizons. Soybeans price heavily influences PMEAL and explains from 55 to 63 percent of PMEAL's FEV at horizons of six months or less. As well, soy meal price is noticeably influenced by soy oil price, with from 20 to 35 percent of PMEAL behavior attributed to variations in POIL at horizons of a year or more. Generally, movements in the three soy-based quantities have, at most, moderate effects on PMEAL, with the collective movements in all three quantities explaining from seven to no more than 24 percent of PMEAL variation at horizons at and surpassing 12 months.

Soy oil quantity is exogenous at shorter run horizons of six months or less when own-variation explains from 58 to 84 percent of QOIL behavior. At horizons of 12 months or more, QOIL becomes increasingly endogenous with own-variation explaining from 40 percent to as little as 16 percent of its behavior. As with the QMEAL and QBEANS, soy oil quantity is heavily influenced by soy-based prices, especially at the longer run horizons. At horizons of 12 months or beyond, own prices (POIL) explains as much as 25 percent of QOIL behavior, while movements in the three prices collectively explain as much as 76 percent of QOIL behavior. Other soy-related quantities contribute negligibly to explaining QOIL behavior at horizons of 12 months and beyond, with neither QBEANS or QMEAL explaining more than about 8 percent of QOIL variation. QMEAL also seems more driven by prices than by quantities.

Soy oil price is generally endogenous at longer run horizons. Own-variation explains from 38 to 56 percent of POIL behavior at horizons below 12 months, and no more than 28 percent at horizons of a year or more. The other two soy-based prices heavily influence POIL's behavior at horizons beyond six months, when PBEANS explains up to 44 percent and PMEAL explains up to 27 percent of POIL's variation. Modeled soy-based quantities collectively explain only from 12 to 14 percent of QOIL's behavior at all reported horizons.

Overall, the FEV decompositions suggest that the three prices appear to drive the three-market soy-based system more than quantities. Collectively, the three soy-based prices explain up to nearly half (47 percent) of QMEAL behavior, while the three soy-based quantities collectively explain no more than 24 percent of PMEAL variation. For the soybeans market, the three prices collectively explain up to about 33 percent of QBEANS behavior, while the three quantities collectively explain no more than 22 percent of PBEANS behavior. Such price-dominated influences are particularly evident from patterns of soy oil FEV decompositions. While the three prices collectively account for as much as 76 percent of QOIL variation, the three quantities collectively explain no more than about 14 percent of soy oil price behavior.

There is some mutual support of impulse patterns from a PMEAL shock (increase) summarized in figure 2 and table 2 and the FEV decomposition patterns in table 3. Table 3's FEV decompositions suggest modest contributions of PMEAL variation to the explanation of QBEANS and PMEAL behavior at horizons of six months and less, which appears to validate (1) our assumption that the first six QBEANS impulses are probably not significantly significant and comprise a half-year reaction time (table 2 and figure 2), and (2) our contention that QMEAL's very short run and negligibly but positively valued monthly impulses are probably unimportant (if even significant statistically). The FEV decompositions in table 3 suggest moderate PMEAL variation contributions to explaining QBEANS and QMEAL movements and relatively more pronounced PMEAL variation contributions to explaining QOIL behavior. These results are generally consistent with figure 2's patterns of PMEAL-induced impulses that are moderate for QMEAL and QBEANS and relatively more pronounced for QOIL. And as well, PMEAL's pronounced and accelerating degrees of influence on PBEANS and POIL over time in table 3's FEV decompositions are consistent with the bell-shaped patterns of pronounced PMEAL-induced impulses for PBEANS and POIL in figure 2.

Summary and Conclusions

We have applied the new DAG/Bernanke VAR methodology developed by Bessler and Akleman (1998) and Haigh and Bessler (2003) to the monthly upstream and downstream U.S. markets for soy-based products (soybeans, soy meal, soy oil). We used the model to generate two sets of VAR econometric results that illuminate the empirical magnitudes of parameters that drive, and the dynamic nature of the monthly interactions among, the U.S. soybean, soy meal, and soy oil markets. First are the impulse responses from simulating the model under a rise in soy meal prices. And second, we provide a set of results from analysis of FEV decompositions.

The shock to (increase in) soy meal price was presumed the result of a BSE-induced rise in demand for soy meal as a feed ingredient and from continually escalating world demands for soy meal's prime ingredient, soybeans, although other sources for the shock on our reduced-form DAG/Bernanke VAR model were plausible. On average historically, each percent rise in PMEAL elicits a 0.5 percent decline in soy meal quantity, a 0.8 percent decline in soybean quantity, and a 1.7 percent rise in soybean price. As well, average historical trends suggest that each percentage rise in PMEAL elicits a 4.6 percent decline in soy oil quantity and a 4 percent rise in soy oil price. The high (absolute) values of the two soy oil market response multipliers may arise from soy oil's minority share of market-clearing soybean volumes and from soy oil's high competition with and substitutability for other vegetable oils in a large number of industrial and consumer uses.

In the shorter run horizons of a year or less, the prices and quantities of the three soy-based products are generally more exogenous than after a year, when the six-variable system increasingly and steadily integrates into a highly endogenous system. Generally at horizons of a year or more, prices seem to drive the system more than quantities: PMEAL, PBEANS, and POIL appear to drive the three quantities more than QBEANS, QMEAL, and QOIL drive the three prices.

A positive shock in soy oil price would likely push prices of soybeans, soy meal, and soy oil higher. As a reduced form model, the DAG/Bernanke VAR suggests that the positive PMEAL shock elicits negative demand side effects which outweigh the positive supply side effects, so that a positive shock in PMEAL results in net decreases in the volumes of all three soy-based quantities which clear the respective markets. FEV decompositions suggest that the primary market forces work more through price movements than movement in quantities.

The most influenced of the three markets from movements in PMEAL or movements in the two other markets appears to be the soy oil market. This high sensitivity of response is suggested by POIL's and QOIL's relatively high levels of endogeneity suggested by the FEV decompositions and the far greater-than-unity POIL and QOIL response multipliers from imposing a PMEAL increase on the VAR. Such sensitivity may arise from soy oil's minority share of pre-crushed soy bean volume, and from the high levels of soy oil competition with non-soy oils in a variety of industrial and consumer uses.

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