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DYNAMIC RELATIONSHIPS AMONG SELECTED U.S. COMMODITY-BASED, VALUE-ADDED MARKETS: APPLYING DIRECTED ACYCLIC GRAPHS TO A TIME SERIES MODEL

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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 quarterly system of U.S. markets: the wheat market and a set of downstream milling and bakery markets that use wheat as an input. Analyses of the model's impulse response simulations and forecast error variance decompositions provide updated estimates of market elasticity parameters that drive these markets, and updated policy-relevant information on how these quarterly markets run and dynamically interact. Results suggest that movements in commodity-based markets strongly influence each other, although most of these effects occur in the long run beyond a single crop cycle. The paper illuminates how important U.S. food prices respond to wheat farm market shocks in price and quantity.

Key words: Bernanke structural VARs, directed acyclic graphs, quarterly wheat-related markets.

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While farm commodity markets have been a focus of much empirical research, the value-added products that use farm commodities have been neglected as an empirically researchable area. Unlike farm commodities such as corn and soybeans generally, the United States Department of Agriculture (USDA) and other Federal agencies often do not publish highly periodic (monthly or quarterly) data on quantities (demanded or supplied) or stocks of value-added products (Babula and Rich 2001, p. 1). Moreover, food industries typically classify data on own prices, production, and distribution as proprietary and confidential, and preclude it from being in the public purview (Babula and Rich 2001, p. 1). There are few studies that estimate the market-driving elasticity parameters for value-added products that use farm commodities, and that illuminate the dynamic interactions between farm commodity markets and related downstream value-added markets. Two exceptions are Rich, Babula, and Romain (2002) and Babula and Rich (2001) which are presented and explained below.

This paper's goal is to address the lack of empirical research on commodity-related and value-added markets. The study applies a new advancement in econometric modeling to a particular set of U.S. markets related to a farm commodity. More specifically, we focus on Bessler and Akleman's (1998) new time series econometric methodology that combines directed acyclic graph (DAG) techniques with Bernanke's (1986) structural vector autoregression or VAR methods (hereinafter, the "DAG/Bernanke VAR" methodology and detailed below). And as an example of the methodology's straightforward applicability to related farm commodity and value-added markets generally, we apply it to the following set of U.S. wheat-related markets: farm wheat market, wheat flour market, mixes and doughs (mixes/doughs), bread, wheat-based breakfast cereals, and cookies and crackers (cookies/crackers). Some quarterly econometric work using more traditional VAR methods than those applied here has been done on wheat-based markets: Babula and Rich (2001) on U.S. durum and related pasta markets and Rich et. al. (2002) on the wheat-related markets just and update and cited. Given the application of the newly developed DAG/Bernanke methodology, this paper is a methodological extension of this prior research.

The remainder of this paper is comprised of several sections. First we specify a quarterly VAR model of the U.S. markets for wheat and certain wheat-based, value-added markets. The choice of a VAR model is justified and diagnostic evidence of the estimated VAR's specification adequacy is presented. Second, we apply Bessler and Akleman's (1998) DAG/Bernanke VAR methodology to a quarterly model of U.S. markets for wheat and five wheat-based, valued-added products downstream. Third, we apply two well-known VAR econometric tools, analysis of forecast error variance (FEV) decompositions and impulse response simulations, to empirically estimate market price elasticities and to illuminate the dynamic quarterly relationships driving these markets and characterizing the markets' interface. A final section of summary and conclusions follows.

Vector Autogregression Model: Specification, Data, Estimation, and Model Adequacy

We extend Rich et al.'s (2002) and Babula and Rich's (2001) recent VAR model analyses on U.S. markets for wheat and wheat-based products by adapting Bessler and Akleman's (1998) methodological combination of DAG-based results on causal orderings in contemporaneous time with Bernanke's structural VAR methods. We first specify a traditional VAR model of seven quarterly wheat-related variables listed below (hereafter, the "first-stage" VAR). Bessler and Akleman's (1998) methodology is applied to the first-stage VAR. The seven endogenous variables (denoted throughout interchangeably by the parenthetical terms) include:

1. Wheat price (PWHEAT)
2. Quantity of wheat demanded/supplied in the U.S. market (QWHEAT)
3. Wholesale price of wheat flour (PFLOUR)
4. Wholesale price for mixes and doughs (PMIXES)
5. Wholesale price of bread in first differences[1] (DIFPBREAD)
6. Wholesale price of wheat-based breakfast cereals (PCEREAL)
7. Wholesale price of cookies and crackers (PCOOKIES)

Economic theory suggests that the U.S. wheat market and the downstream markets for wheat-based value-added products interact and influence each other (Rich et. al 2002; Babula and Rich 2001). What is not theoretically evident, however, is just how, with what dynamic quarterly patterns, and to what ultimate degrees, that such interrelationships take place. In particular, we focus on how shocks in certain wheat-related prices and in QWHEAT influence each other and pulsate downstream through the markets for wheat-using processed products. While conventional theoretically-based or "structural" econometric models are equipped to address questions at static equilibria before and after an imposed shock, they often have little to say about what happens dynamically between pre- and post-shock equilibria (Sims 1980; Bessler 1984m, pp. 110-111). VAR econometric methods are well-equipped to address policy-relevant dynamic issues of what unfolds between pre- and post-shock equilibria. VAR econometric methods impose as few a priori theoretical restrictions as possible so as to permit the regularities in the data to reveal themselves. More specifically, these regularities will provide information on the four "dynamic aspects" of how wheat and wheat-based markets respond to wheat market shocks, and how they interact with each other, on a quarterly basis: (1) direction of the responses, (2) magnitude of a respondent variable's ultimate change, (3) quarterly patterns which the responses of the variable take, and (4) the strength of relationships among wheat-related variables.

Specification Issues

Detailed derivations and summaries of VAR econometric methods are provided by Sims (1980), Bessler (1984), Hamilton (1994, ch. 11) and Patterson (ch. 14), and are not provided here. Tiao and Box's (1978) lag selection methods were applied to the above vector of endogenous variables, and evidence suggested a one-order lag structure. And consequently, the seven-equation, first-stage VAR model is specified as :

$$\begin{aligned}(1)\ X(t) = {} & a_0 + a_{x1}*PWHEAT(t\text{-}1) + a_{x,2}*QWHEAT(t\text{-}1) + a_{x,3}*PFLOUR(t\text{-}1) \\ & + a_{x,4}*PMIXES(t\text{-}1) + a_{x,5}*DIFPBREAD(t\text{-}1) + a_{x,6}*PCEREAL(t\text{-}1) \\ & + a_{x,7}*PCOOKIES(t\text{-}1) + R_x(t)\end{aligned}$$

Above, the parenthetical terms denote a value's time period: t for the current period and t-1 for the one-order quarterly lagged value. The a-terms are regression coefficient estimates. Of the two subscripts, x refers to the x-th equation, while the numeric subscript refers a variable. The nought-subscripted a-term refers to the intercept. X(t) = PWHEAT(t), QWHEAT(t), PFLOUR(t), PMIXES(t), DIFPBREAD(t), PCEREAL(T), and PCOOKIES(t). $R_x(t)$ are the x-th equation's estimated white noise residuals.

[1] For reasons presented below, evidence suggests that bread price is nonstationary and is modeled in first differences.

Following previous VAR econometric work on quarterly U.S. wheat-related markets, each of the seven VAR equations contains a time trend and three seasonal binary variables. As well, an event-specific binary variable is defined for each of three events: the 1989 implementation of the Canada/U.S. Free Trade Agreement, the 1994 implementation of the North American Free Trade Agreement or NAFTA, and the U.S. tariff rate quotas imposed on U.S. imports of Canadian durum and non-durum wheat for the year ending September 11, 1995 (Rich et. al. 2002; Babula and Rich 2001; Babula, Jabara, and Reeder 1996; and USITC 1994).

All data were defined for the June 1 - May 31 U.S. wheat "market year." Hence, a "split" year, say 2000/2001, refers to the U.S. market year beginning June 1, 2000 and ending May 31, 2001.[2] Quarterly market year data for the seven endogenous variables were collected over the 1985/86:1 through 2002/2003:2 period. The model was estimated over the 1986/87:1– 2002/2003:2 period because the four quarterly observations for 1986/87 were "saved" for a Tiao/Box lag search. Following previous work, the VAR model was estimated with ordinary least squares in logarithms so that shocks to and impulse responses in the logged variables reflect approximate proportional changes in nonlogged variables (USITC 1994, ch. II; Rich et. al. 2002; and Babula and Rich 2001, p. 5).

Hamilton (1994, p. 324-327) noted that a VAR model may be considered a reduced form of a structural econometric system. Hence, QWHEAT and the modeled wheat-related prices are not the quantities and prices specifically demanded or specifically supplied, but rather are prices and quantities that clear the market (Hamilton 1994, pp. 324-327; Rich et. al. 2002, p. 102). So any simulation's shock-induced changes in a price or quantity are actually net changes after all, and sometimes countervailing, effects of supply and demand have played out (Rich et. al. 2002, p. 102; Babula and Rich 2001, p. 5).

Reliable quarterly data on U.S. supply, consumption, or stocks were not available for wheat flour,[3] mixes and doughs, bread, wheat-based breakfast cereals, and cookies/crackers. Following recent quarterly VAR econometric research on U.S. wheat-related markets, we invoked the VAR model's well-known reduced form properties and modeled wheat-based, value-added food markets with reduced form price relationships (Rich et. al. 2002; Babula and Rich 2001). Considering that reliable quarterly data are not available for quantities (stocks or production) in the wheat-based downstream markets, we follow this prior research and model each of the wheat-based valued-added markets with a single reduced-form price equation that captures as much of the respective market's elements of demand and supply as limited data permit (Babula and Rich, p. 5).

Cointegration

The model was estimated as a VAR model where all seven endogenous variables except bread price were estimated in natural logarithms, and where bread price, because of evidence that logged levels

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[2] Throughout, the marketing year quarters are denoted by numerals to the right of the split year and colon. Considering 1998/99 as an example: 1998/99:1 refers to the quarter spanning June, July, and August of 1998; 1998/99:2 refers to the quarter spanning September, October, and November, 1998; 1998/99:3 refers to the quarter spanning December 1998, and January and February of 1999; and 1998/99:4 is the quarter spanning March, April, and May, 1999.

[3] The U.S. Department of Labor's Bureau of the Census (Labor, Census 1985-2002) publishes U.S. stocks and production of wheat flour in its quarterly and annual summary issues of *Current Industrial Reports, Flour Milling Products*. We followed Rich et. al. (2002, p. 102) and did not use this data as the quality and accuracy of the data are in serious question. First, a major U.S. miller stated that the data on wheat flour stocks and production were unreliable in a telephone conversation with an author. And second, these contentions were confirmed by the staff of the *Milling and Baking News* (2000, pp. 1 and 19) in a front-page article concerning inaccuracies of these data.

were nonstationary, was incorporated in first differences of logged levels. This VAR framework was chosen over a vector error correction (VEC) model suggested by Johansen and Juselius (1990, 1992). This is because evidence emerged from the logged levels data to suggest that cointegration was likely not an issue, since all but one of the seven endogenous (in logged levels) were stationary.

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, augmented Dickey-Fuller (ADF) $T\mu$ tests were conducted on the logged levels of the VAR model's seven endogenous variables.[4] We followed recent VAR econometric research on quarterly models of U.S. wheat-related markets and concluded that a variable was likely stationary when ADF $T\mu$ test evidence at the 10 percent significance level (hereafter 10% level) was sufficient to reject the null hypothesis of nonstationarity.[5] While insufficient to reject the null hypothesis of nonstationarity for bread price, ADF $T\mu$ evidence at the 10% level was sufficient to reject the null hypothesis that each of the following six variables was nonstationary in logged levels, leading to our decision to treat these as stationary: PWHEAT, QWHEAT, PFLOUR, PMIXES, PCEREAL, and PCOOKIES.[6] As a result, with six of the seven variables treated as stationary, we concluded that cointegration was not an issue, and that a VAR model of the following was appropriate: logged levels of PWHEAT, QWHEAT, PFLOUR, PMIXES, PCEREAL, PCOOKIES; first differences of logged bread price levels or DIFPBREAD.

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

[5] This criterion of a 10 percent significance level was chosen over the five percent level because of well-known ADF test problems in generating results biased towards nonstationarity when, as in this study, samples are finite and/or when an otherwise stationary variable has a root approaching unity and is "almost nonstationary." (See Harris 1995, pp. 27-29; and Kwiatowski et. al. 1992). Harris (1995) and Kwiatowski et. al. (1992) recommend that in cases where samples are moderate in size and/or variables are "almost nonstationary," such variables should be treated as stationary and should not be differenced. We followed Rich et. al. and chose a 10 percent significance level for the ADF $T\mu$ tests to avoid bias toward nonstationarity.

[6] The following five ADF $T\mu$ values suggest that evidence is actually sufficient at the 5% (as well as 10%) level to reject the null of stationarity, because in each case, the test value was negative and had an absolute value in excess of that of the ADF $T\mu$ critical value of -2.89: PWHEAT (-3.4), QWHEAT(-6.7), PMIXES (-3.65), PCEREAL (-2.96), and PCOOKIES (-3.1). With a $T\mu$ value of -2.59, evidence was sufficient at the 10% level to reject the null hypothesis that PFLOUR in logged levels was nonstationary. Rich et al. (2002, pp. 101-103) conducted further tests on this variable using methods of Sargan and Bhargava (1983) and Kwiatowski et. al. (1992), and concluded that evidence suggested that PFLOUR is nonstationary. These previous test results plus our ADF evidence led to our conclusion that PFLOUR should be treated as a stationary variable. The ADF $T\mu$ test on nondifferenced, logged levels of bread price generated a test value of -1.1, which reflected evidence that was insufficient at the 5% or 10% levels to reject the null hypothesis of nonstationarity [the value was negative but had an absolute value far below that of the critical value of -2.89]. Consequently, bread price was treated as nonstationary and modeled as a variable of first differences of logged levels of bread price, DIFPBREAD.

Sources of Quarterly Data and Data Issues

QWHEAT, the U.S. market-clearing quantity available of wheat, is the sum of beginning stocks, production, and imports, and are published by the USDA (2002, 2003).[7] As noted in Rich et. al. (2002, p. 103), each equation's quarterly seasonal binary variables play an important role for two reasons. First, wheat is a seasonal commodity and numerous VAR econometric analyses on U.S. wheat-related markets have placed seasonal binaries in such equations (USITC 1994, ch. II; Rich et al. 2002, p. 103; and Babula and Rich 2001). Second, the seasonal binary variables are crucial in accounting for the annually-recurring, production-induced QWHEAT spike in each year's initiating quarter.

All six prices were converted into market year quarterly data from monthly data and then placed into natural logarithms. A number of quarterly U.S. wheat-based product prices were calculated from the following monthly producer price indices (PPI) published by the U.S. Department of Labor, Bureau of Labor Statistics (Labor, BLS 2003): PFLOUR from the PPI for wheat flour (series no. PCU2041#1); PMIXES from the PPI for flour mixes and refrigerated and frozen doughs and batters (series no. PCU2045#6); PCEREAL from the PPI for wheat flakes and other wheat breakfast foods (series no. PCU2043#112); and PCOOKIES from the PPI for cookies and crackers (series no. PCU2052#). Quarterly DIFPBREAD data were obtained by taking monthly PPI data for bread (series no. PCU2051#1) from Labor, BLS (2003); converting data levels into market year quarterly values; logging these values; and then first-differencing the logged levels.

Diagnostic Evidence Supporting Adequacy of VAR Model Specification

For reasons established in Sims (1980) and Bessler (1984), the VAR model was appropriately estimated with ordinary least squares (or OLS) over the 1986/87:1-2002/2003:2 quarterly sample period using Doan's (1996) RATS software. Following previous quarterly econometric analysis on U.S. wheat-related markets, the model was as judged adequately specified based on evidence from Ljung-Box portmanteau and DF unit root tests on the residual estimates of the seven 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 (see Granger and Newbold 1986, pp. 99-101). With seven portmanteau values [ranging from 12.6 to 25.1] falling below the critical chi-square value of 32.0, evidence at the 1% significance level is clearly insufficient in each case to reject the null hypothesis of model adequacy, leading to the conclusion that the VAR model was adequately specified.

Granger and Newbold (1986, pp. 99-101) caution against the exclusive reliance on the portmanteau tests for model adequacy. Consequently, Dickey-Fuller (or DF) $T\mu$ unit root tests were conducted on each VAR equation's residual estimates since stationary residual estimates also provide evidence of adequate model specification (Rich et. al. 2002, pp. 104-105; Babula and Rich 2001, p. 7).

[7] QWHEAT was defined to include primarily Canadian imports as well as U.S. supplies because of strong evidence that emerged from previous research that U.S. millers and merchants consider similarly classed consignments of Canadian and U.S. wheat as highly, if not perfectly, substitutable (USITC 1994, p. II.83 and appendix M; Babula and Jabara 1999, pp. 90-91). This valuable evidence was based on highly reliable U.S. International Trade Commission (USITC) questionnaire work the reliability of which was enhanced by the USITC's option to subpoena non-respondents of the questionnaires (Babula and Jabara 1999, pp. 90-91). Previous research concluded that an increase in highly/perfectly substitutable imports of Canadian wheat had the same basic effects on U.S. price as increases in U.S.-produced supplies of wheat (USITC 1994, ch. II and appendix N; Babula and Jabara 1999, pp. 90-91). Consequently, we placed imports in with U.S. wheat supply to form QWHEAT, just as the researchers of quarterly U.S. wheat-related markets recently did (USITC 1994; Babula et. al. 1996; Rich et. al. 2002; Babula and Rich (2001).

With DF Tμ values ranging from -6.8 to -9.8 and a critical value of -2.89, evidence at the 5% level is clearly sufficient in each of the seven cases to reject the null hypothesis of nonstationarity, and to conclude that the seven equations are adequately specified. The combined Ljung-Box and DF test evidence on the estimated VAR equation residuals suggests that the VAR model is adequately specified by the evidentially-based standards established in the literature.

We specified and estimated a first-stage VAR of the seven endogenous wheat-related variables. Now we will transform this first-stage VAR into a "DAG/Bernanke" structural VAR using Bessler and Akleman's (1998) application methods.

Directed Acyclic Graphs

The above VAR modeling methods make thorough use of lagged causal relationships among PWHEAT, QWHEAT, PFLOUR, PMIXES, DIFPBREAD, PCEREAL, and PCOOKIES. These wheat-related variables are clearly correlated in contemporaneous time as well, although the VAR methods outlined above, in themselves, say little or nothing about such contemporaneous correlation (Bessler 1984, p. 114). It is well known that ignoring causal orderings among a VAR's endogenous variables in contemporaneous time may produce impulse response simulations and forecast error variance or FEV decompositions that are not representative of observed market relationships (Sims 1980; Bessler 1984, p. 114; Saghaian et. al. 2002, p. 104). Traditionally, VAR econometric work has accounted for contemporaneous correlation in two principal ways. First is the Choleski factorization, the most traditionally applied method, where contemporaneous orderings are through imposition of a theoretically-based and recursive Wold causal ordering imposed on the VAR's variance/covariance matrix (Bessler 1984, p. 114; Bessler and Akleman 1998, p. 1144). Rich et. al. (2002) provided a Choleski-based ordering of this paper's same set of seven endogenous variables. The second and more recent approach to handling orderings of endogenous variables in contemporaneous time is the application of Bernanke's structural VAR methods where prior notions of (hopefully) evidentially-based and/or theoretically-based causal orderings in contemporaneous time may be imposed on a VAR's endogenous variables (Bessler and Akleman 1998, p. 1144). And as noted by Bessler and Akleman (1998, p. 1144), a problem with a Choleski-based approach is that a recursive ordering may be overly restrictive, while a problem with Bernanke's approach is that the true contemporaneous orderings which the researcher claims to know by assumption may be unknown.

We invoke Bessler and Akleman's methodology where the DAG analysis of Scheines et. al. (1994) and Spirtes et. al. (2000) is used to glean a system of contemporaneous causal relations supported by data-embedded evidence, and the causal relations are then imposed on a Bernanke-type structural VAR. Saghaian et. al. (2002, p. 104) note that these methods provide evidentially-based patterns of contemporaneous correlations for analysis of impulse responses and innovation accounting methods that are reasonable given the data set. We thereby avoid excessive reliance on recursive restrictions and/or on expert opinions inherent in contemporaneous orderings of more traditional Choleski-ordered or Bernanke structural VAR models.

We apply DAG methods to the seven U.S. wheat-related variables and impose the DAG-suggested lines of contemporaneous orderings on the VAR. The DAG/Bernanke structural VAR then generates results from analyses of impulse responses and FEV decompositions that provide crucial parameter estimates for these markets, and that illuminate the dynamic quarterly relationships driving the system of seven U.S. wheat-related market variables.

Directed Graphs and the PC Algorithm

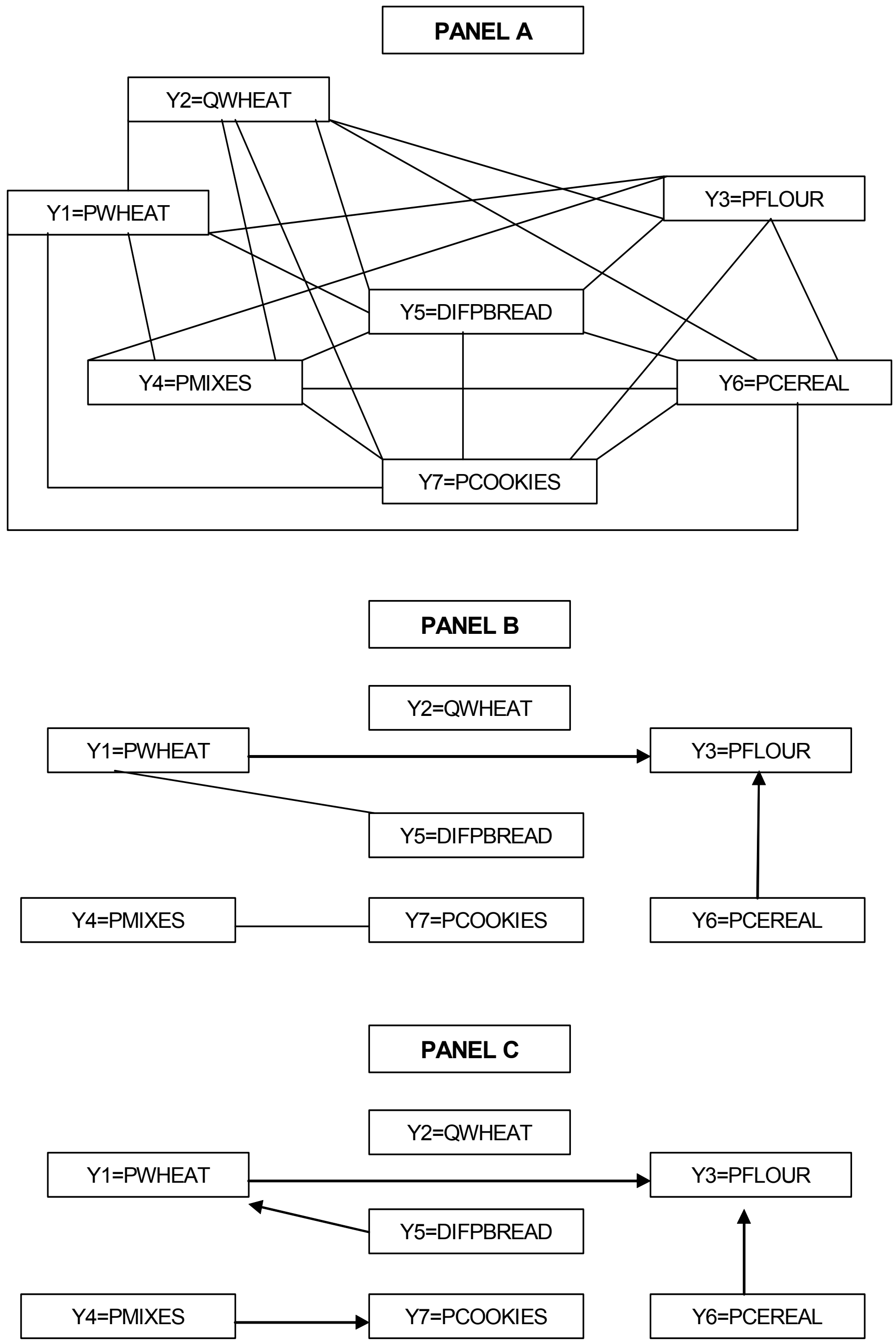
The application of directed acyclic graphs follows the theoretical work given in Pearl (2000) and the TETRAD algorithms described in Spirtes, Glymour, and Schines (2000). Following Bessler and Akleman (1998), we apply the TETRAD II PC algorithm to construct a DAG on innovations from a first stage VAR model.

The PC algorithm is an ordered set of commands that begins with a general unrestricted set of relationships among variables (errors from each VAR equation) and proceeds stepwise to remove edges between variables and to direct causal flow. Briefly, one begins with a complete, undirected graph G on the vertex set, V, where the complete undirected graph shows an undirected edge between every variable in the system (every variable in V) (Bessler and Akleman 1998, p. 1145; Jonnala, Fuller and Bessler 2002, p. 115). Edges between variables are removed sequentially based on zero correlation or partial (conditional) correlation. The conditioning variable(s) on removed edges between two variables is called the sepset, as defined in Bessler and Akleman (1998, p. 1144-1146), of the variables whose edge has been removed (for vanishing zero-order conditioning information, the sepset is the empty set). Edges are directed by considering triples X – Y – Z, such that X and Y are adjacent, as are Y and Z, but X and Z are not adjacent. One directs edges between the triples X – Y – Z as X→Y ← X if Y is not in the sepset of X and Z. If X→Y, Y and Z are adjacent, and X and Z are not, and there is no arrowhead at Y, then orient Y – Z as Y → Z. If there is a directed path from X to Y and an edge between S and Y, then direct X – Y as X →Y. The PC algorithm is marketed as the software TETRADII (Scheines et. al.).

DAG Applications to the System of Seven Endogenous Variables

Here, we apply DAG methods to order the seven endogenous variables in contemporaneous time. Hereafter, the seven variables are denoted interchangeably by the parenthetical Y-terms: PWHEAT (Y1), QWHEAT (Y2), PFLOUR (Y3), PMIXES (Y4), DIFPBREAD (Y5), PCEREAL (Y6), and PCOOKIES (Y7). The starting point is panel A of figure 1, the completely undirected graph of all possible edges between the seven variables. Panel B provides the edges that TETRAD II suggests as statistically nonzero at the chosen level (here 10%) of significance. There is a two-stage, and possibly three-stage, process for gleaning data-based evidence to causally order the seven endogenous variables in contemporaneous time. First, the TETRADII algorithm (see Scheines et. al. 1994 and Spirtes et. al. 2000) analyzes unconditional correlations and eliminates all statistically zero edges and retains all statistically nonzero correlations. Second, the TETRADII algorithm further analyzes all remaining conditional correlations, eliminates such conditional correlations that are statistically zero, and retains the statistically nonzero ones. Panel B in figure 1 provides the edges retained in these two stages. Were these retained edges in panel B fully directed (which they are not), we would have a unique set of correlations to be imposed on Bessler and Akleman's (1998) DAG/Bernanke VAR model covariance matrix. But figure 1(B) provides some edges that are directed, and some which are undirected, giving rise to several competing systems of observationally equivalent contemporaneous causality relationships. In such cases, there is a third stage of the analysis developed by Haigh and Bessler (2003): they modified and applied Schwarz's (1978) loss metric, applied it to the alternative systems of causality, and then chose the system of causality which minimizes the Schwartz metric (panel C of figure 1 as detailed below). The metric-minimizing system of relationships (panel C, figure 1 as stated below) is imposed on the DAG/Bernanke model.

Figure 1
Complete undirected graph (Panel A), TETRAD-generated graph (Panel B), and final DAG (Panel C) on innovations from the VAR model of 7 wheat-related variables



Source: Analysis of the authors.

The quarterly, market year sample ranges from 1986/87:1 through 2002/2003:2, the estimation period for the VAR model. Innovations (ϵ_{it}) from the VAR outline 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 (Σ or any correlation matrix) are the negatives of the partial correlation coefficients between the corresponding pair of variables, given the remaining variables in the matrix (Whittaker 1990; Bessler and Akleman 1998, p. 1146). So for example, computing the conditional correlation between innovations ϵ_{1t} and ϵ_{2t}, given ϵ_{5t} would entail calculation of the inverse of the 3*3 matrix Σ_1 (taking corresponding elements from Σ). The off-diagonal elements of the scaled inverse from this matrix are the negatives of the partial correlation coefficients between the corresponding pair of variables, given the remaining variables (Bessler and Akleman 1998, p. 1146). Under the assumption of multivariate normality, Fisher's Z statistic may be used to test the hypothesis of each element being statistically nonzero (Bessler and Akleman 1998, p. 1146; Jonala, Fuller, and Bessler 2002, p. 115).

Table 1 provides the essentials for stages 1 and 2 of the TETRAD analysis. The correlation matrix (lower triangular innovation correlation matrix) was generated by the OLS-estimated VAR model. Each of the elements are correlations denoted as "rho" with rho(1,3) denoting the correlation between Y1 and Y3. The p-values for these corrlations are provided in the second lower triangular matrix. Basically, all edges with a p-value above 0.10 for the chosen 10% significance level are removed. This leaves the following five edges [bottom of table 1 and graphed in panel B of figure 1]:

- PWHEAT(Y1) →PFLOUR(Y3): a directed edge where wheat price influences or causes flour price (rho(1,3) = +0.915, p-value < 0.10).

- PCEREAL(Y6) → PFLOUR(Y3): a directed edge where wheat-based breakfast cereals influences/causes wheat flour price (rho(3,6) = 0.214, p-value < 0.085) level.

- PWHEAT(Y1) – DIFPBREAD(Y5): an undirected edge where wheat and bread prices are interrelated (rho(1,5) = +0.231, p-value = 0.061) This edge has two observationally equivalent possibilities: Y5 → Y1 or Y1 → Y5.

- PMIXES(Y4) – PCOOKIES(Y7): an undirected edge where prices of mixes/doughs and of cookies/crackers are interrelated. The rho(4,7) of +0.217 has a 0.08 p-value falling below the 0.10 value reflective of the 10% significance level. Here, this edge has two observationally equivalent possibilities: Y7 → Y4 or Y4 → Y7.

- QWHEAT (Y2) is exogenous.

Since some of these TETRADII-generated edges are ambiguously directed, some have more than one observational equivalent, as noted above. These results generate the four plausible systems of causality as the unambiguous edges (first, third, and fifth) are combined with the ambiguous third and fourth edges with more than a single observational equivalent. One attempts to choose among these four possible and competing systems of causal relations detailed in table 2. Table 2's non-intercept regressors and dependent variables are the respective variable's VAR-generated residual estimates. For example, "Y1 = const, Y5" implies that Y1 → Y5 in contemporaneous time. An exogenous variable would have the intercept, const., as the only right-side regressor. These regressions of sets of residuals map-out the

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

Y1	Y2	Y3	Y4	Y5	Y6	Y7
1.00						
-0.44	1.00					
0.92	-0.42	1.00				
-0.05	0.09	-0.10	1.00			
0.23	0.02	0.16	-0.05	1.00		
0.10	-0.08	0.21	-0.03	-0.15	1.00	
-0.08	-0.06	-0.13	0.22	-0.03	-0.14	1.00

P-Values for Correlations:

Y1	Y2	Y3	Y4	Y5	Y6	Y7
0.00						
0.0002	0.00					
0.0000	0.0003	0.00				
0.71	0.476	0.413	0.00			
0.061	0.86	0.213	0.668	0.00		
0.421	0.52	0.085	0.829	0.228	0.00	
0.512	0.634	0.299	0.08	0.784	0.271	0.00

"Salvaged" Edges: 10% Significance Level:

PWHEAT or Y1 → PFLOUR or Y3
PWHEAT or Y1 — DIFPBREAD or Y5
PCEREAL or Y6 → PFLOUR or Y3
PMIXES or Y4 — PCOOKIES or Y7
QWHEAT or Y2 = exogenous

Source: Authors' analyses of TETRAD II and regression results.

Table 2
Four Alternative (Observationally Equivalent) Systems of Contemporaneous Causal Relations that Emerge from TETRADII-Suggested Edges;

System 1	System 2	System 3	System4
Y1 = const.	Y1 = const.	Y1 = const., Y5	Y1 = const., Y5
Y2 = const.	Y2 = const.	Y2 = const.	Y2 = const.
Y3 = const., Y6, Y1	Y3 = const., Y6, Y1	Y3 = const., Y6, Y1	Y3 = const., Y6, Y1
Y4 = const.	Y4 = const., Y7	Y4 = const.	Y4 = const., Y7
Y5= const., Y1	Y5 = const., Y1	Y5 = const.	Y5 = const.
Y6 = const.	Y6 = const.	Y6 = const.	Y6 = const.
Y7 = const., Y4	Y7 = const.	Y7 = const., Y4	Y7 = const.
Schwarz value = -63.9	Schwarz value = -61.9	Schwarz value = -64.9	Schwarz value = -62.9

Notes.—Note that all equalities refer to regressions of the VAR model residuals of the endogenous variable against a constant or intercept, "const.", and the VAR model residuals of the other relevant variables. For example: the third equation in each system regresses the residuals of Y3 or PFLOUR against an intercept, the residuals of Y6 or PCEREAL, and the residuals of Y1 or PWHEAT. Note that Y1 through Y7 refer to the VAR model residuals of, respectively, PWHEAT, QWHEAT, PFLOUR, PMIXES, DIFPBREAD, PCEREAL, and PCOOKIES. See Schwarz (1978) and Haigh and Bessler (2002) for details of how Schwarz's loss metric was applied to the above four competing systems of contemporaneous causal relations to score and then choose among them.

Source: Authors' application of Haigh and Bessler's (2003) regression methodology.

possible four causal systems which are implied and compete for our choice from the five edges that emerged from TETRADII's analysis.[8]

Schwarz's (1988) loss metric modified and adapted by Haigh and Bessler was used to score the four alternative, competing systems of causal relationships in table 2. The score for each model is provided in table 2, and arises from (Haigh and Bessler 2003):

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

Σ^* is a diagonal matrix with diagonal elements of the variance/covariance matrix associated with a linear representation of the disturbance terms from an acyclic graph fit to innovations from the VAR model. The third system was chosen because it minimized the Schwartz loss metric (with an algebraically minimal value of -64.9). The following are the third system's relationships that were imposed onto the Bernanke structural VAR to form the DAG/Bernanke VAR model, so as to resolve the issue of contemporaneous correlation:

- DIFBPREAD or Y5 → PWHEAT or Y1.
- QWHEAT or Y2 is exogenous, as are the following that do not "receive" an arrow (← or →): PMIXES or Y4, DIFPBREAD or Y5, and PCEREAL or Y6.
- PCEREAL or Y6 →PFLOUR or Y3 ← PWHEAT or Y1.
- PMIXES or Y4 → PCOOKIES or Y7.

Analysis of Simulation Results of the DAG/Bernanke VAR Impulse Response Function for a PWHEAT Increase and a QWHEAT Decline

A VAR econometric tool that is useful in applied work is the impulse response function which simulates, over time, the effect of a one-time shock in one of the system's series on itself and on other series in the system (Bessler 1984; Hamilton 1994, ch. 11; Goodwin and McKenzie 2003). This is done by converting the VAR model into its moving average (MA) representation (Hamilton 1994, ch. 11). The parameters of the MA representation are complex combinations of the VAR regression coefficients (Bessler 1984). One uses the impulse responses to discern what the sample's long run and average regularities would proscribe as the dynamic nature of the response patterns of modeled endogenous variables to an imposed shock in another endogenous variable.

Using literature-established methods, multipliers are calculated from each simulation's statistically relevant responses. The multipliers are similar to elasticities and indicate history's long run average percentage change in a responding variable per percentage change in a shock variable. [See Babula and Rich (2001, p. 10) for calculation details.] Sign is important: a positive value suggests that

[8] Haigh and Bessler (2002) note that one applies Schwarz's loss function because scoring the, here four, alternative models results in the same log determinant for each alternative acyclic model. Alternative models merely move correlations from the diagonal elements to the off-diagonal elements in the residual covariance matrix from alternative models. And accordingly, one scores alternatives using the residual covariance matrix.

each percentage change in the shock variable directionally coincided with the shock variable changes, while a negative value suggests that a variable response was in the opposite direction of the shock.

Following Bessler, Yang, and Wongcharupan (2002, p. 819), we do not calculate confidence intervals on the impulse response functions. Although such is not a difficult task for a VAR ordered with a Choleski decomposition, calculating standard errors of impulse response functions for a Bernanke structural VAR is much more challenging and is left for future research. Yet clearly, one needs an indicator of impulse significance, such as the Kloek-VanDijk routines built into Doan's (1996) package for Choleski-ordered VAR impulse simulations. This is because often only a very small subset of all calculated impulses typically achieves significance (see Babula and Bessler 1987 as an example). Fortunately, Rich et. al. (2002) recently modeled the same seven endogenous variables as a Choleski-ordered VAR. We applied the duration times (typically, 3 or 4 quarters) from Rich et. al.'s analysis (2000) to establish the ranges of our impulses that were statistically nonzero.[9]

We simulated the DAG/Bernanke VAR's impulse response function in the following two ways:[10]

Simulation 1: imposed an exogenous, presumably tariff-induced increase (one orthogonalized standard error, 7.23%) on PWHEAT to examine the dynamic aspects of quarterly response patterns in QWHEAT, PFLOUR, PMIXES, PCEREAL, and PCOOKIES.

Simulation 2: imposed an exogenous, presumably quota-induced, decline (one orthogonalized standard error, 9.7%) on QWHEAT to examine the dynamic aspects of quarterly response patterns in PWHEAT, PFLOUR, PMIXES, PCEREAL, and PCOOKIES.

Recent VAR econometric research pointed out that there is some subjective leeway in identifying the source of shocks imposed on this (or any) reduced form model (Babula and Rich 2001, p. 10). While the assumed sources of the shocks in the simulations are valid, the shocks to the PWHEAT and QWHEAT variables could have arisen from other sources, since the VAR model's estimated reduced-form relations are neither prices nor quantities supplied or demanded, but rather prices or quantities which clear the market after a full interplay of all, and often counterbalancing, demand and supply adjustments (Hamilton 1994, ch. 11; Babula and Rich 2001, pp. 10-11). That is, other sources could have generated

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[9] Given Rich et. al.'s (2002) evidence that only the first 3 or 4 of their quarterly impulses from PWHEAT and QWHEAT shocks on the same modeled system achieved statistical significance at the 10% level, we conclude that treating all 12 of our responses as signifcant would be unrealistic and would (perhaps recklessly) disregard recent and related research done previously with more traditional methods.

[10] Throughout, we follow Rich et. al. (2002) and do not analyze the dynamic attributes of DIFPBREAD in either simulation. This variable was included for purposes of adequacy of specification, and since it was necessary to so-include it in first differences, interpretation of this variable's impulses is not straightforward. Also following Rich et. al. (2002), we attempted a number of other impulse response simulations, but little or no statistically significant responses emerged. This was clearly due to the aggregation of the data. Shocking one of the downstream value-added wheat-based prices, say PCOOKIES or PCEREAL, use only part of the QWHEAT aggregate (a sum of five U.S. wheat classes), so that such downstream price shocks will elicit little response in QWHEAT and PWHEAT. And since the downstream prices often use different wheat classes, then shocking downstream prices does little to elicit significant responses in other downstream products. Shocking downstream prices, which use or are relevant to only portions of the QWHEAT and PWHEAT aggregates, is like "shooting pool with a marble." However, QWHEAT aggregates over the five wheat classes are the USDA's only fully and regularly published wheat data. Further, shocking QWHEAT and PWHEAT makes more sense, insofar as shocks to these 5-class aggregates do logically influence less aggregated wheat-based value-added markets downstream.

the same shocks. The shock in PWHEAT, presumed here as tariff-induced, could have arisen from, say, changes in production costs. Simulation 2's shock of a QWHEAT decline, presumed here as quota-induced, could have arisen from perhaps a drop in yields or production.

As expected, an increase in PWHEAT induces a series of declines in wheat quantity, with these quarterly decreases declining in magnitude and lasting a year. On average historically, each percentage rise in PWHEAT elicits a 0.5 percent decline in wheat quantity as the tendency for declines in demand tend to more than offset rises in production in the reduced form setting. Flour price rose: impulses lasted for about a year and registered, on average historically, increases of about 0.4 percent for each percentage rise in PWHEAT. Based on recent previous findings from Rich et. al.'s (2002) Choleski-ordered VAR of the same system, PWHEAT increases generally do not elicit rises in the prices further downstream of mixes/doughs, wheat-based breakfast cereals, and cookies/crackers.

A presumably quota-induced fall in QWHEAT was imposed on the DAG/Bernanke's impulse response function as the second simulation. As expected, the decline in QWHEAT elicited about a year's worth of wheat price increases, with the quarterly price increases taking a bell-shaped pattern. On average historically, each percentage drop in QWHEAT elicited a 0.4 percent rise in wheat price. Flour price increased with the drop in QWHEAT: PFLOUR increases lasted 3 quarters and registered increases of about 0.14 percent for each percentage drop in QWHEAT.

Analysis of Forecast Error Variance Decompositions

Analysis of decompositions of forecast error variance or FEV is a well-known VAR innovation accounting method for discerning relationships among the modeled system's time series (Sims 1980; Bessler 1984). As Bessler (1984, p. 111) noted, analysis of FEV decompositions is closely related to Granger causality analysis as both tools provide evidence concerning the existence of a causal relationship among two variables. But analysis of FEV decompositions goes further than Granger causality tests. Since a modeled endogenous variable's FEV is attributed at alternative horizons to shocks in each modeled variable (including itself), analysis of FEV decompositions not only provides evidence of the simple existence of a relationship among two variables, but it also illuminates the strength and dynamic timing of such a relationship (Bessler 1984, p. 111; Babula and Rich 2001, pp. 14-15; Saghaian et. al. 2002, p. 107). Such measures are useful in applied work. Table 3 provides the FEV decompositions for the VAR model estimated above for the seven wheat-related variables. These FEV decompositions reflect the causal relationships embedded in both the lagged VAR model and the chosen causal ordering among the seven variables in contemporaneous time using Bessler and Akleman's (1998) DAG/Bernanke VAR modeling methods. A variable is endogenous (exogenous) when large (small) proportions of its FEV are attributed to variation of other modeled variables (itself) (Bessler 1984).

Wheat price is clearly an endogenous player in the system, particularly at midterm and longer term horizons. Own-variation accounts for 66% to 80% of the PWHEAT's movements at horizons of 2 quarters or less, but these high levels of short run exogeneity rapidly fall to about 33% at the longer run horizons. Movements in PFLOUR and bread price collectively account for as much as 40% of PWHEAT's behavior at the longer run horizons. The impact of PFLOUR and DIFPBREAD over the long term on PWHEAT likely reflects the downstream demand conditions. Over the long term, the demand for flour and bread products would impact the demand, and hence the price, of wheat. As expected, QWHEAT also influences PWHEAT. Variation in the prices of wheat-based breakfast cereals, cookies/crackers, and mixes and doughs have minor influences on PWHEAT. This lack of influence on PWHEAT may be explained by two factors. The data aggregation issues, addressed earlier, may explain the lack of influence, insofar as each price may reflect classes of wheat which aggregate into only a minority share of the 5-class PWHEAT "all-wheat" aggregate. And secondly, for wheat-based breakfast

Table 3
Decompositions of forecast error variance generated by the DAG/Bernanke VAR model

Variable explained	Horizon	PWHEAT	QWHEAT	PFLOUR	PMIXES	DIFPBREAD	PCEREAL	PCOOKIES
		Percent of forecast error variance explained by						
PWHEAT	1	79.92	5.22	3.32	0.47	10.35	0.31	0.41
	2	66.08	8.74	8.12	0.84	14.28	0.92	1.03
	4	47.85	12.45	15.59	1.11	18.14	2.63	2.25
	6	38.86	13.77	20.50	1.19	19.08	4.47	3.12
	8	34.46	14.11	21.34	1.24	19.10	6.10	3.65
	9	33.21	14.13	21.82	1.25	10.01	6.78	3.80
QWHEAT	1	12.40	84.38	1.54	0.18	1.46	0.00	0.03
	2	17.34	73.56	4.34	0.21	4.38	0.08	0.06
	4	19.03	60.80	9.56	0.25	9.15	0.79	0.42
	6	18.04	54.40	12.94	0.32	11.52	1.91	0.88
	8	16.94	51.00	14.84	0.38	12.55	3.06	1.23
	9	16.52	49.94	15.41	0.40	12.81	3.57	1.34
PFLOUR	1	75.36	2.28	8.70	2.21	9.30	2.09	0.16
	2	64.71	5.24	8.82	3.19	14.70	2.78	0.54
	4	46.34	9.53	14.31	3.27	20.64	4.47	1.44
	6	37.25	11.24	18.05	2.98	22.16	6.26	2.06
	8	33.11	11.74	19.80	2.82	22.32	7.84	2.38
	9	31.99	11.80	20.64	2.72	22.15	9.47	2.45
PMIXES	1	2.23	0.30	3.89	86.94	6.17	0.1	0.36
	2	6.06	0.87	5.87	70.20	9.03	0.29	0.67
	4	12.10	0.94	6.05	70.45	9.17	0.50	0.80
	6	14.95	1.31	6.,14	67.23	9.10	0.49	0.79
	8	15.74	2.05	6.96	64.24	9.56	0.55	0.89
	9	15.78	2.40	7.43	62.98	9.78	0.64	0.99
DIFPBREAD	1	0.89	2.48	0.00	1.43	95.98	0.05	0.02
	2	1.42	2.87	0.04	2.51	91.74	0.10	0.09
	4	2.49	2.91	0.13	3.03	90.94	0.20	0.30
	6	3.25	2.85	0.14	3.01	89.87	0.24	0.64
	8	3.6	2.90	0.25	2.98	88.85	0.24	1.08
	9	3.67	2.95	0.35	2.97	88.51	0.25	1.31
PCEREAL	1	0.00	0.14	0.25	0.46	0.76	97.89	0.50
	2	0.07	0.12	0.68	0.64	2.53	94.58	1.38
	4	0.43	0.10	1.16	0.58	6.51	87.25	3.97
	6	0.68	0.11	1.13	0.51	9.38	80.94	7.25
	8	0.72	0.16	1.04	0.55	11.22	75.68	10.63
	9	0.70	0.19	1.01	0.59	11.90	73.41	12.20
PCOOKIES	1	1.46	1.76	0.17	8.48	2.95	0.04	85.15
	2	2.70	1.72	0.52	9.63	5.69	0.07	79.68
	4	5.42	1.28	0.79	9.06	10.58	0.10	72.76
	6	7.68	1.04	0.64	7.95	15.36	0.08	67.24
	8	9.14	1.13	0.70	7.06	19.54	0.10	62.34
	9	9.61	1.26	0.84	6.71	21.27	0.13	60.19

cereals, cookies/crackers, and mixes/doughs, wheat represents only a minor part of the ingredient inputs of such products. Non-wheat inputs account for significant shares of ingredient costs for these wheat-based, valued-added products.

With more than 70% of QWHEAT behavior attributed to own-variation at shorter run horizons, the variable is highly exogenous in the short run. Yet as time progresses, own-variation's importance as an explanator of QWHEAT behavior falls steadily to about 50 percent. Aside from own-variation, the three most important explanators of QWHEAT behavior are movements in prices of important wheat-based value-added products, which collectively account for more than 40 percent of QWHEAT during the longer terms: own-price (up to 19 percent); wheat flour price (15 percent); and bread price movements (up to nearly 13 percent) at the longer horizons. Similar explanations for the importance of PFLOUR and DIFPBREAD on PWHEAT at the longer run horizons apply here to QWHEAT.

Wheat flour price's most important influence is not own-price, which explains no more than about 21 percent of PFLOUR variation, but rather movements in wheat price. Wheat price's contributions to explaining flour price variation range from 75% at shorter run horizons down to 32 percent at the longer run horizons. Bread price variation accounts for more than 20 percent of PFLOUR variation at most horizons, while variation in wheat quantity explains nearly 12 percent of PFLOUR behavior at some longer term horizons. Only minor proportions of PFLOUR variation may be attributable to prices of mixes/doughs, bread, wheat-based breakfast cereals, and cookies/crackers.

As noted by Babula and Rich (2001), prices of highly processed wheat-based products tend to be increasingly exogenous with higher proportions of variation attributed to own-variation as one travels further downstream from the farm gate. Such is expected as industrial, labor, marketing, and other costs not directly modeled here take on increasing importance, and while movements in QWHEAT and PWHEAT have decreasing influence, on overall production costs.

The price of mixes and doughs is highly exogenous to the system, with no less than 63% of its behavior self-attributed. Nonetheless and of some interest, wheat price movement provides a noticeable explanatory contribution by explaining up to 16 percent at the longer term horizons. Movements in bread price, PCEREAL, and PCOOKIES individually have minor influences on PMIXES behavior. Interestingly, while PMIXES behavior is noticeably driven by PWHEAT movements, QWHEAT variation has little to say about PMIXES behavior, suggesting that producers of mixes/doughs gauge production decisions on wheat price variation, but at the longer run horizons.

Bread price behavior is predominately explained by own-variation, which accounts for at least 89 percent of DIFPBREAD behavior at all reported horizons. One might consider the lack of significant influence of PWHEAT and QWHEAT on DIFPBREAD troubling. Given the importance of wheat flour, and thus wheat, as a bread ingredient, one may expect the price and quantity of wheat to have more effect on bread price behavior. However, as with other manufactured products, bread prices tend to be sticky. Thus, declines in wheat costs generally do not result in comparable declines in bread prices, but are captured by the various producers along the production chain. The reverse may also hold. Sharp price increases in wheat may be less likely to be passed onto the consumer, and more likely to be shouldered by the producers. This is demonstrated by the recent sharp increases in wheat prices as a result of drought in the United States and Canada that failed to result in comparable increases in the price of bread.[11] These factors tend to minimize the impact of wheat quantity and price shocks on bread price behavior.

[11] For example, during the period May 2002 to October 2002, the ingredient index for white pan bread calculated by BakingBusiness.com increased brom 101.7 to 138, while the PPI for bread, as reported by the BLS and used in this model increased by far less, from 232.8 to 234.6.

At all horizons, no less than 73% of PCEREAL's behavior is attributed to own-variation, a high level of exogeneity potentially explained by already-proffered factors such as the importance of non-wheat ingredient inputs and the stickiness of manufactured value-added products . Interestingly, the variation in the prices of bread and of cookies/crackers collectively explain about a quarter of PCEREAL's movements at the longer run horizons. And these lines of causality appear one-way: PCOOKIES and DIFPBREAD influence cereal prices, although PCEREAL contributes virtually nothing to the explanation of the behavior of DIFPBREAD and PCOOKIES. An explanation of these conditions is unclear. One may expect all three products to generally move together in an upward trend. Perhaps the impact of DIFPBREAD and PCOOKIES on PCEREALS results from such tandem trending, or from the impact of omitted variables (e.g. labor, utility, and transport costs common to grain-based production generally), although these factors do not rationalize the one-way nature of the causality patterns. The lack of the feedback effects of these variables on DIFPBREAD is discussed below.

PCOOKIES is highly exogenous, with from 60% to 85% of its behavior attributed to own-variation. Aside from own-variation, bread price behavior is the most important explanator (up to 21% of) PCOOKIES behavior. As well, up to more than 15% of PCOOKIES' variation is collectively attributed to variation in wheat and mixes/doughs prices. That mixes/doughs are intermediate inputs in production of some cookies and some bread may cause one to expect that PMIXES' variation influences behavior of both PCOOKIES and bread price. And while PMIXES does influence PCOOKIES, there is no appreciable effect on bread price behavior. Moreover, DIFPBREAD appears to influence PMIXES (up to 10%). Here again, we are confronted with conditions that could be rationally explained, except for the apparent disconnects in causality.

A review of the impact of DIFPBREAD across all variables yields an intriguing observation. Bread price behavior accounts for at least 10 percent, and up to about 20 percent, of the variation of all endogenous variables except QWHEAT at the longer run horizons, with such implied patterns of causality being one-way with little or no feed-back influence on DIFPBREAD. Additionally, bread price was the only modeled variable that seems to have a unit root and pursue a random walk, which necessitated its inclusion in first-difference form. This may imply that bread price is an efficient price where there is no appreciable predictability of its behavior from its past, and as with any random walk, the best prediction of bread price is its current value. Samuelson (1965) concluded that a properly anticipated price for an efficient market follows a random walk; perhaps this implies a higher level of market efficiency for bread relative to the other modeled wheat-based downstream products. Compared with the other modeled wheat-based value-added markets, the bread market has a more competitively structured production sector with is more numerous and competing firms producing a homogeneous product. Additionally, bread is universally traded by more than 90 percent of American households, and appears to follow a random walk, thereby fulfilling Samuelson's (1965) arguments that the market may be relatively more efficient. Bread prices do not seem to return to a constant historical mean, while other value-added wheat-based prices do. This may imply that DIFPBREAD appears to be a widely watched and widely discussed information or "strategy" variable for the grain-based foods industry as a whole. This could also rationalize the otherwise unexpected correlation between DIFPBREAD and other grain-based food variables. That is, producers of the other less competitively structured value-added products may look to bread price behavior, an efficient process generated by numerous bread producers, for guidance in "administering" their other wheat-based value added product prices. It would also rationalize the one-way nature of the bread price-related causality patterns. Needless to say, these are only conjectures, and are offered as directions for future research.

Summary and Conclusions

There are two sets of VAR econometric results generated by our DAG/Bernanke VAR model that illuminate the empirical magnitudes of market parameters that drive, and the dynamic nature of the quarterly interface among, selected wheat-related markets of the United States. First are the impulse response simulations of a PWHEAT increase and a QWHEAT decrease. A second set of results emerged from analysis of the FEV decompositions.

The shock to (increase in) wheat price, whether tariff-induced or not, and the shock to (decrease in) wheat quantity, whether quota-induced or not, do not seem to affect much more than their own wheat market and the first (wheat flour) market downstream, and during the short run of a single crop cycle or market year. Yet Doan (1996, p. 8.13) strongly warns against use of impulse response analysis alone and without accompanying analysis of FEV decompositions. Analysis of FEV decompositions, however, extends the analysis beyond a single market year into the longer run time frames. And FEV decompositions clearly demonstrate that at longer run horizons, (1) behavior in the wheat market clearly becomes manifest in wheat-using markets downstream, and (2) perhaps more interestingly, events in the wheat-based, value-added product markets downstream importantly influence the wheat market. So while looking at the impulse response results may suggest that wheat market shocks do not have noticeable influences on wheat-based value-added markets far downstream, FEV decompositions clearly suggest that such wheat markets have important effects on the downstream markets over the longer horizons beyond a single crop cycle. And further, despite little or no influence suggested by the impulse response results, FEV decompositions clearly suggest that movements in the downstream wheat-based markets have marked effects on the wheat market at longer run horizons.

These interactive impacts from shocks or events in the upstream and downstream markets may have a variety of sources. On the demand side, wheat-based products may compete for constrained flows of consumer expenditures. On the supply side, different wheat-based product markets may compete for constrained stocks of similarly classed wheat supplies; may use wheat classes that in turn compete for limited planted area as do durum and hard red spring production in the Northern Plains; and/or for constrained quantities of other non-agricultural inputs. Explaining these interdependencies at the longer run horizons is a productive area of future research.

A rise in PWHEAT, presumed here as tariff-induced but which may emerge from a rise in perhaps production costs, results in about a market year's worth of QWHEAT declines that, on average historically, register as a 0.5 percent drop for each percentage rise in PWHEAT. As well and over the same time frame, flour price rises, on average, 0.4 percent per percent rise in PWHEAT. A QWHEAT decline, presumed here as quota induced but which may also emerge from variation in production or yields, results in nearly a market year's worth of PWHEAT increases that, on average historically, add up to about 0.4 percent for each percentage drop in QWHEAT. The QWHEAT decline, over the same time frame, also elicits a rise in PFLOUR that averages 0.14 percent for each percentage point drop in QWHEAT. Further downstream beyond the flour market, these impulse response simulations do not appear to have much of an impact within the time horizon of a single market year.

But the FEV decompositions extend the analysis and show a complex array of one-way and multi-directional causal influences between the wheat and wheat-using markets beyond the short run horizon of a single market year or crop cycle. One general point that emerges from analysis of FEV decompositions is that shocks and movements in upstream/downstream wheat-based markets are felt in all wheat-based markets when time is ample for shock effects to become manifest. Perhaps the time frames required to contract new factor supplies, contract new sales agreements, and to expand fixed assets in response to such shocks and movements require horizons extending beyond a single crop year.

PWHEAT, QWHEAT, and PFLOUR, as expected, share a complex web of bidirectional causal influences as seen from table 3. Further, movements in price and quantity of wheat contribute importantly to the explanation of behavior in most of the remaining downstream product prices, although this influence seems to wane, in percentage terms, as the degree of value-added processing inherent in the wheat-based product rises. For example, FEV decompositions suggest that, QWHEAT and PWHEAT movements collectively explain from 43% to more than nearly 80% of PFLOUR variation, and for no more than about 11 percent of PCOOKIES variation.

Bread price movements contribute importantly to variation in all other modeled variables, including PMIXES, PLFOUR, PCEREAL, and PCOOKIES, although movements in these latter four prices have little influences on bread price behavior (table 3). As well, downstream market influences seem to importantly influence the wheat market, with variation in flour, bread, breakfast cereal, and cookies/crackers prices collectively accounting for nearly half of PWHEAT variation and for nearly 30% of QWHEAT variation at the longer run horizons.

The QWHEAT and PWHEAT are the only wheat market variables for which fully detailed situation - and - outlook tables are published. The downstream markets use less aggregated wheat classes: for example, cookies/crackers production uses softer wheat classes with low protein contents, while bread production uses harder wheat classes with higher protein content. So one expects an effect from the more aggregated variables to the downstream variables. And one may expect some feedback from certain downstream markets to the upstream wheat market. However, given the aggregated nature of PWHEAT and QWHEAT, some of the interrelationships among downstream prices in table 3 may either arise from competitive factors (competition for substitutable wheat supplies or for wheat-producing acreage) or perhaps simply from a pass-through relationship through movements in more aggregated PWHEAT and QWHEAT variables. In other words, are prices of mixes/doughs and cookies/crackers interrelated because they compete for similar wheat consignments and/or use wheat classes competing for common farm acreage, or simply because they are related on a pass-through basis as the 5-class aggregates in PWHEAT or QWHEAT move. This is another area of recommended future research.

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