Journal of Agricultural and Applied Economics, 36,1(April 2004):1–22

Dynamic Relationships Among U.S. Wheat-Related Markets: Applying Directed Acyclic Graphs to a Time Series Model

Ronald A. Babula, David A. Bessler, and Warren S. Payne

Using advanced methods of directed acyclic graphs with Bernanke structural vector autoregression models, this article extends recent econometric research on quarterly U.S. markets for wheat and wheat-based value-added products downstream. Analyses of 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 wheat and downstream wheat-based markets strongly influence each other, although most of these effects occur at the longer-run horizons beyond a single crop cycle.

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

JEL Classifications: C22, Q11

The value-added side of the food industry, unlike farm commodity markets, has been neglected as an empirically researchable area, in part because of a lack of published data on these industries. Unlike commodities such as corn or soybeans, the United States Department of Agriculture (USDA) and other Federal agencies often do not publish highly periodic (monthly or quarterly) data on quantities (demanded or supplied) or stocks of value-added products (Babula and Rich, p. 1). Moreover, food industries typically classify information on own prices, production, and distribution as confidential and thereby preclude it from the public purview (Babula and Rich, p. 1). Consequently, there are few studies that estimate the market-driving elasticity parameters for wheat-based value-added products, and that illuminate the dynamic nature of quarterly interactions among U.S. wheat and wheat-based value-added markets. Two recent empirical contributions to this generally lacking area of value-added, commodity-based market research are Rich, Babula, and Romain's (hereafter, RBR's) time series econometric study on the U.S. markets for wheat

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Ronald A. Babula is an industry economist, Agriculture and Forest Products Division, United States International Trade Commission, Washington, DC. David A. Bessler is professor, Department of Agricultural Economics, Texas A&M University, College Station, TX. Warren S. Payne is an international trade analyst, Agriculture and Forest Products Division, United States International Trade Commission, Washington, DC.

The authors thank two anonymous reviewers for many helpful comments and suggestions that improved the paper. As well, the authors are grateful to Ms. Phyllis Boone of the Agriculture and Forest Products Division, United States International Trade Commission, for her expert help in preparing this study's tables and figure. The opinions expressed herein are those of the authors and are not those of the U.S. International Trade Commission or any of its Commissioners, or of Texas A&M University.

and wheat-using value-added products downstream, and Babula and Rich's analysis of the U.S. markets for durum wheat, semolina, and pasta. However, RBR is a conference proceedings paper published in a largely unavailable volume, and without any benefit of peer review.

This paper contributes to the literature in two ways. First, a time series analysis is performed on the U.S. wheat market and for wheat-using markets downstream (downstream markets). Given the lack of empirical econometric research just cited, this article helps to fill this gap of research by providing an analysis on these important U.S. markets in the peer-reviewed literature. We ultimately provide updated estimates of important wheat-related market parameters and updated results that illuminate the dynamic nature with which upstream and downstream wheat-related markets interact, particularly for the RBR analysis.[1] Second, this paper extends the studies of RBR and Babula and Rich with the application of new methods of directed acyclic graphs (hereafter DAGs). These new graphical procedures generate evidentially based lines of causality among variables in contemporaneous time for the U.S. markets of wheat and wheat-using value-added products. These downstream markets include wheat flour, mixes and doughs (hereafter, mixes/doughs), bread, breakfast cereals, and cookies and crackers (hereafter, cookies/crackers). More specifically, our analysis has the advantage of having adapted the recently developed econometric procedures, as applied to U.S. beef and pork prices by Bessler and Akleman, to a quarterly system of U.S. wheat-related markets. This set of procedures combines DAGs with Bernanke's methods of structural vector autoregression (VAR) modeling and is hereafter denoted as the "DAG/Bernanke VAR" procedures.

The remainder of this paper is comprised of several sections. First is a summary of why updating and extending the research of RBR and Babula and Rich on U.S. wheat-related markets is important and newsworthy, and hence of interest to this journal's readership. Second, we specify a quarterly VAR model of the U.S. markets for wheat and certain wheat-based value-added markets. We provide evidence that most of the modeled variables are stationary in logged levels, to justify our choice of a VAR model over a vector error correction model of Johansen and Juselius (1990, 1992). In addition, diagnostic evidence of the estimated VAR's specification adequacy is presented. Third, we introduce Bessler and Akleman's DAG/Bernanke VAR procedures and apply them to a quarterly model of U.S. markets for wheat and five wheat-based valued-added products downstream. In the fourth and fifth sections, we apply two well-known VAR econometric tools, analysis of selected impulse response simulations and forecast error variance (FEV) decompositions, to empirically estimate market price elasticities and to illuminate the dynamic quarterly relationships driving these markets and characterizing the markets' interface. A summary and conclusions follow.

Relevance and Newsworthy Nature of the Wheat-Based Product Issues

There has been a longstanding, visible, and contentious array of debates by U.S. and Canadian Federal trade and agricultural authorities concerning U.S. imports of (primarily Canadian) wheat. Falling under the "large country" assumption, the United States encompasses substantial wheat-producing and wheat-using sectors with often opposing views on the desirability of wheat imports and of quantity or protection measures on such imports (see Alston, Gray, and Sumner 1994, 1999; Babula and Jabara; Babula, Jabara, and Reeder; Seidband; and U.S. International Trade Commission [USITC] 1990, 1994). Generally, wheat producers find U.S. imports of wheat undesirable and favor quotas, tariffs, or duties placed on such imports. Milling and

[1] Although published as a book of conference proceedings in 2002, the Rich, Babula, and Romain paper was actually presented at an October 1999 conference in Fargo, ND, and the analysis spanned only the calendar year 1999. There was nearly a 2-year lag between the conference's occurrence and the proceedings' publication in 2002, such that our update was more of one than one may infer from the RBR publication date. As well, the work did not benefit from peer review.

baking interests are often in favor of unfettered U.S. wheat imports and oppose quotas, tariffs, or duties imposed on such imports. The relevance and newsworthiness of such issues are reflected by the following trade investigations or events that occurred since 1990:

- A recent antidumping/countervailing duty investigation filed by U.S. (particularly North Dakota) wheat growers against imports of Canadian hard red spring and durum wheat (U.S. Department of Commerce; *Wall Street Journal* Staff).
- A year-2001 section 332 fact-finding investigation by the U.S. International Trade Commission or USITC examining allegedly questionable and/or unreasonable wheat trading practices by the Canadian Wheat Board (USITC 2001).
- A year-2000 section 301 investigation by the U.S. Trade Representative or USTR of U.S. imports of Canadian hard red spring and durum wheat (USTR).[2]
- A 1995 study on the U.S./Canadian wheat trade by a Canada/U.S. Commission on Grains, which resulted in separate tariff rate quotas imposed by the United States on certain imports of nondurum and durum wheat for the year ending September 11, 1995 (Glickman and Kantor.)
- A 1994 section-22 investigation by the USITC on whether U.S. imports of primarily Canadian durum and nondurum wheat materially injured the U.S. farm program for wheat (see USITC 1994).[3]
- A 1990 section-332 fact-finding investigation by the USITC (1990) on the competitive conditions of the U.S. and Canadian durum wheat industries.

We argue that using new and advanced econometric methods to generate policy-relevant evidence and information would be of interest to agents on both sides of the debate over U.S. wheat imports, including U.S. and Canadian agriculture and trade authorities, agribusiness agents, and researchers. Such policy-relevant evidence and information includes updated estimates of U.S. wheat market parameters, little-known estimates of price response multipliers for wheat-based markets downstream, results that illuminate how wheat market shocks dynamically influence wheat-related markets, and information on how downstream wheat-related markets dynamically influence the wheat market.

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

We extend RBR's and Babula and Rich's recent VAR model analyses on U.S. markets for wheat and wheat-based products by adapting Bessler and Akleman's 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 procedures are applied to the first-stage VAR. The seven endogenous variables (denoted throughout interchangeably by the parenthetical terms) are:

1. Wheat price (PWHEAT)
2. Quantity of wheat demanded/supplied in the U.S. market (QWHEAT)

[2] A "section 301" investigation is filed under section 301, Chapter 1 of Title 3 of the Trade Act of 1974 (19 U.S.C. subsection 2411 et seq.) and concerns investigations by USTR of allegations that foreign countries are denying benefits to the United States under trade agreements or are otherwise engaged in unjustifiable, unreasonable, or discriminatory acts that burden or restrict U.S. commerce. Generally, USTR may initiate a section 301 investigation upon petition by any interested party or upon its own initiative. See USITC (1998, p. 29).

[3] Under section 22 of the Agricultural Adjustment Act (U.S.C. subsection 624), if the Secretary of Agriculture has reason to believe that an article that is being imported into the United States is materially interfering with a USDA farm program, or is substantially reducing U.S. production and/or processing of a related product, the USDA advises the President who, should he agree with the allegations, then requests the USITC to conduct an investigation on the matter. The USITC compiles an advisory report for the President who then acts. See USITC (1998, p. 26).

3. Wholesale price of wheat flour (PFLOUR)
4. Wholesale price for mixes and doughs (PMIXES)
5. Wholesale price of bread in first differences[4] (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 (Babula and Rich; RBR). However, what is not theoretically evident is just how, with what dynamic quarterly patterns, and to what ultimate degrees, such interrelationships take place. In particular, we focus on how shocks in PWHEAT and in QWHEAT influence each other and pulsate downstream through the markets for wheat-using, processed products. Whereas 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 postshock equilibria (Bessler, pp. 110–11; Sims). VAR econometric methods are well-equipped to address policy-relevant dynamic issues of what unfolds between pre- and postshock equilibria. VAR econometric methods impose as few a priori theoretical restrictions as possible to permit the regularities in the data to reveal themselves. More specifically, these regularities will provide information on the four "dynamic aspects" of how shocks in PWHEAT and QWHEAT influence the wheat market and the downstream markets for wheat-based products: (1) direction of the responses, (2) magnitude of a respondent variable's ultimate change, (3) quarterly patterns that the responses of the variables take, and (4) the strength of relationships among wheat-related variables.

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

Specification Issues

The system was estimated as a VAR model in logged levels (except for DIFPBREAD) because cointegration was not an issue. As shown below, unit root test results suggest that six of the seven variables are likely stationary in logged levels.

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

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

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 xth equation, whereas the numeric subscript refers to 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). $\epsilon_x(t)$ are the xth equation's estimated white noise residuals.

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 ("dummy") 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, and the U.S. tariff rate quotas imposed on U.S. imports of certain Canadian durum and nondurum wheat for the year ending September 11, 1995 (Babula and Rich; Babula, Jabara, and Reeder; RBR; 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.[5] Quarterly market year data for the seven endogenous variables were collected over the 1985/1986:1 through 2002/2003:2 period. The model was estimated over the 1986/1987:1–2002/2003:2 period because the four quarterly observations for 1986/1987 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 (Babula and Rich, p. 5; RBR; and USITC 1994, ch. II).

Hamilton (pp. 324–27) 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, pp. 324–27; RBR, 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 (Babula and Rich, p. 5; RBR, p. 102).

Reliable quarterly data on U.S. supply, consumption, or stocks were not available for wheat flour,[6] 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 (Babula and Rich; RBR). We acknowledge that modeling each of these downstream markets with both quantity and price variables would have been superior. But 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 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 variables (in logged levels) were stationary.

When a vector system of individually non-

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

[6] 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 RBR (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* (pp. 1 and 19) in a front-page article concerning inaccuracies of these data.

stationary 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.[7] 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% significance level (hereafter 10% level) was sufficient to reject the null hypothesis of nonstationarity.[8] Although 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.[9] 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.

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, Economic Research Service (2002, 2003).[10] As noted in RBR (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 (Babula and Rich; RBR, p. 103; and USITC 1994, ch. II). Sec-

[7] For details on Dickey–Fuller and augmented Dickey–Fuller tests, see Dickey and Fuller, Fuller, and the test procedure summaries in Hamilton.

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

[9] 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. RBR (pp. 101–03) conducted further tests on this variable using methods of Kwiatowski et al. and Sargan and Bhargava, 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.

[10] 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 (Babula and Jabara, pp. 90–91, and USITC 1994, p. II.83 and Appendix M). 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 nonrespondents of the questionnaires (Babula and Jabara, 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 (Babula and Jabara, pp. 90–91, and USITC 1994, ch. II and Appendix N). 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 (Babula and Rich; RBR).

ond, the seasonal binary variables are crucial in accounting for the annually recurring production-induced QWHEAT spike in each market 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 2002): 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 (2002); 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 and Bessler, the VAR model was appropriately estimated with ordinary least squares (or OLS) over the 1986/1987:1–2002/2003:2 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 on the basis of evidence from Ljung–Box portmanteau and Dickey–Fuller (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, pp. 99–101). With seven portmanteau values (ranging from 8.1 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 (pp. 99–101) caution against the exclusive reliance on the portmanteau tests for model adequacy. Consequently, 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 (Babula and Rich, p. 7; RBR, pp. 104–105). With DF $T\mu$ 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.

Additionally, time-variance of estimated parameters from structural change does not appear to be a problem with our first-stage VAR model estimates. RBR (pp. 106–108) applied a battery of tests for structural change for our same first-stage VAR model estimated for a similar sample and found that evidence was insufficient to suggest structural change. Given that their tests were done on our same first-stage VAR model and for a similar sample, and to conserve space, we did not replicate their analyses here and refer to their evidence.

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 procedures.

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, 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 FEV decompositions that are not representative of observed market relationships (Bessler, p. 114; Saghaian, Hassan, and Reed, p. 104; Sims).

Traditionally, VAR econometric work has accounted for contemporaneous correlation in three 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, p. 114; Bessler and Akleman, p. 1144). RBR provided Choleski-based orderings of this paper's same set of seven endogenous variables. The second approach is the application of Bernanke's structural VAR methods where prior notions of (hopefully) evidentially based or theoretically based (or both) causal orderings in contemporaneous time may be imposed on a VAR's endogenous variables (Bessler and Akleman, p. 1144). Having noted that Choleski-ordered VAR models generate impulse response and FEV decomposition results that may vary with the Wold causal ordering chosen for the decomposition, Pesaran and Shin developed a third approach, a generalized impulse response analysis for VAR models (and for cointegrated models as well) that avoids orthogonalization of shocks and that generates order-invariant results. And as noted by Bessler and Akleman (p. 1144), a problem with a Choleski-based approach is that the world may not be recursive, whereas a problem with Bernanke's approach is that the true contemporaneous orderings that the researcher claims to know by assumption may be in fact unknown. Doan (2002, p. 4) recommends caution when using Pesaran and Shin's generalized impulse response analysis because of difficulty in interpreting impulses from highly correlated shocks within a nonorthogonalized setting. As well, Doan (2002, p. 4) adds that Pesaran and Shin's methods are equivalent to computing shocks with each variable in turn being set atop a Choleski ordering.

Here we extend RBR's unrefereed work on U.S. wheat-related markets based on traditional VAR methods by updating the quarterly sample, re-estimating their model with recent econometric advancements, and bringing the work to the refereed literature with the benefit of full peer review. We use Bessler and Akleman's procedures where the DAG analysis of Scheines et al. and Spirtes, Glymour, and Scheines is used to employ data evidence to help in choosing a set of contemporaneous causal relations from a set of theoretically consistent alternatives. We then impose the evidentially supported causal relations on a Bernanke-type structural VAR.[11] Saghaian, Hassan, and Reed (p. 104) note that these methods provide evidentially based patterns of contemporaneous correlations for analysis of impulse responses and innovation accounting results that are reasonable given the data set. We are thereby able to avoid excessive reliance on recursive restrictions and/or on expert opinions in choosing among competing, yet theoretically consistent, contemporaneous orderings when building more traditional Choleski-ordered or Bernanke structural VAR models.

In this section, 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

[11] We make a few points here in response to comments by an anonymous reviewer. Standard microeconomic theory would sanction the use of at least several competing orderings among the seven modeled wheat-related variables. The DAG-suggested ordering that emerges below is one of these that one could have chosen. The benefit of DAG methods is that it engages data-embedded evidence to help choose among such a set of theoretically sanctioned orderings. It is important to choose the optimal ordering because, as pointed out by Pesaran and Shin, VAR model results vary with the choice of imposed ordering. Bernanke's methods would use theory to impose an ordering that the researcher arbitrarily chooses from the theoretically justified set. The DAG/Bernanke procedures of Bessler and Akleman use data evidence, along with theory, to choose among the same set of orderings.

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. Such is done by analysis of impulse response simulations and FEV decompositions that emerge from the DAG/Bernanke structural VAR.

Directed Graphs and the PC Algorithm

The application of DAGs follows the theoretical work of Pearl and the TETRAD algorithms described in Spirtes, Glymour, and Scheines. Following Bessler and Akleman, we apply the TETRADII 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, p. 1145; Jonnala, Fuller and Bessler, p. 115). Edges between variables are removed sequentially on the basis of zero correlations or partial (conditional) correlations. The conditioning variable(s) on removed edges between two variables is called the sepset, as defined in Bessler and Akleman (pp. 1144–46), 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 X and Y, then direct X—Y as X → Y. The PC algorithm is marketed as the software TETRADII (Scheines et al.).

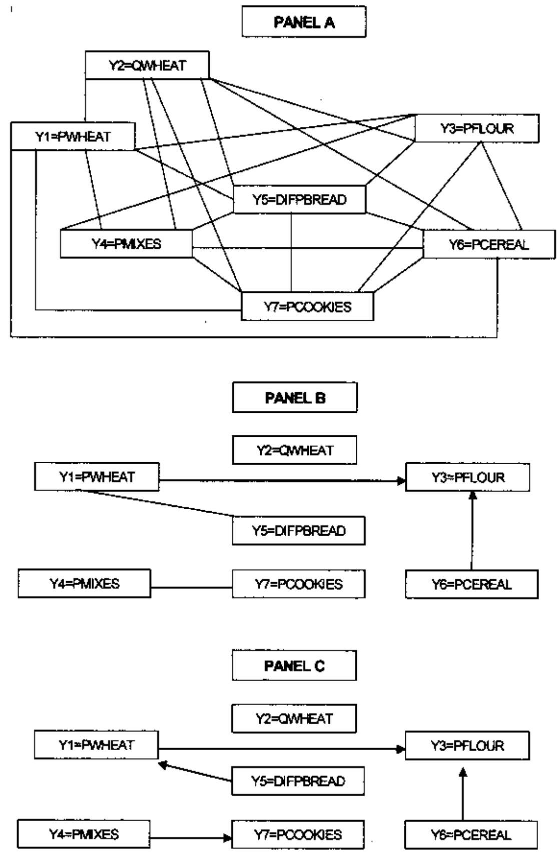

Figure 1. Complete Undirected Graph (Panel A), TETRAD-Generated Graph (Panel B), and Final DAG (Panel C) on Innovations from the VAR Model of 7 Wheat-Related Variables

DAG Applications to the System of Seven Endogenous Variables

Here, we illustrate the application of the DAG methods in sorting out how the seven endogenous variables are ordered 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 TETRADII suggests as statistically nonzero at the chosen level (here 10%) of significance. There is a two-stage or possibly three-stage process for gleaning data-based evidence to establish contemporaneous causal orderings among the seven endogenous variables in contemporaneous time. First, the TETRADII algorithm analyzes unconditional correlations, eliminates all statistically zero edges, and retains all statistically nonzero correlations (see Scheines et al.; Spirtes, Glymour, and Scheines). 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 DAG/Bernanke VAR model covariance matrix. But Figure 1, panel B provides some edges that are directed, and some that 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: They modified and applied Schwarz's loss metric, applied it to the alternative systems of causality, and then chose the system of causality that 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.

The quarterly market-year sample ranges from 1986/1987:1 through 2002/2003:2, the estimation period for the VAR model. Innovations (ϵ_{it}) from our 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 (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 (Bessler and Akleman, p. 1146; Whittaker). 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, 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, p. 1146; Jonnala, Fuller, and Bessler, p. 115).

Table 1 provides the essentials for stages 1 and 2 of the TETRADII 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) [or rho(3, 1) as they are symmetric and equal] denoting the correlation between Y1 and Y3. The p-values for these correlations 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) $\rightarrow$ PFLOUR(Y3): a directed edge where wheat price influences or causes flour price. Recall that rho(1, 3) = +0.92 with a p-value of about zero, and hence far less than 0.10 reflected by the chosen 10% significance level.
- PCEREAL(Y6) $\rightarrow$ PFLOUR(Y3): a directed edge where the price of wheat-based breakfast cereals influences or causes wheat flour price. The rho(6, 3) = 0.21 has a p-value of 0.085, falling below the 0.10 reflected by the chosen 10% significance level.
- PWHEAT(Y1)—DIFPBREAD(Y5): an undirected edge where wheat price and movements in bread prices are interrelated. The rho(5, 1) of +0.23 has a 0.061 p-value, falling below the value of 0.10 for the chosen 10% significance level. Here, this edge has two observationally equivalent possibilities: Y5 $\rightarrow$ Y1 or Y1 $\rightarrow$ Y5.
- PMIXES(Y4)—PCOOKIES(Y7): an undirected edge where prices of mixes/doughs and of cookies/crackers are interrelated. The rho(7, 4) of +0.22 has a 0.08 p-value falling

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

Y1	Y2	Y3	Y4	Y5	Y6	Y7
Correlation and Covariance Matrix						
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						
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

Note: "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.

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. 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. We must choose among these four possible and competing systems of causal relations detailed in Table 2. Table 2's nonintercept regressors and dependent variables are the re-

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

System 1	System 2	System 3	System 4
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. Y1 through Y7 refer to the VAR model residuals of, respectively, PWHEAT, QWHEAT, PFLOUR, PMIXES, DIFPBREAD, PCEREAL, and PCOOKIES.

spective variable's VAR-generated residual estimates. Hence, "Y1 = const, Y5" implies that Y5 → Y1 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 possible four causal systems that are implied and compete for our choice from the five edges that emerged from TETRADII's analysis.

Schwarz's 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 is summarized in Haigh and Bessler:

$$\text{(2)} \qquad SL^* = \log(|\Sigma^*|) + k \log(T)/T,$$

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. We chose the third system, as it minimized the Schwarz loss metric (with the 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:

- 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.

Imposing these relationships resolves the problem of contemporaneous correlation.

Analysis of Simulation Results of the DAG/Bernanke VAR Impulse Response Function: Presumed Tariff-Induced Rise in PWHEAT and Quota-Induced QWHEAT Decline

An important tool of VAR econometrics that is useful in applied work is the impulse response function that 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; Hamilton, ch. 11). This is done by converting the VAR model into its moving average (MA) representation (Hamilton, ch. 11). The parameters of the MA representation are complex combinations of the VAR regression coefficients (Bessler). By imposing a one-time exogenous shock on one of the VAR variables, one may obtain a sort of dynamic map of how the modeled endogenous variables respond to the shock (Goodwin, McKenzie, and Djunaidi). More specifically, examination of the impulse response patterns illuminates the dynamic nature and patterns of quarterly responses of the VAR model's endogenous variables when one of the endogenous variables is shocked (here changes in PWHEAT or QWHEAT).

Using literature-established methods, multipliers are calculated from each simulation's statistically nonzero responses that emerge from the two simulations (a PWHEAT increase and a QWHEAT decrease and described below).[12] 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. Sign is important: A positive multiplier suggests that each percentage change in the

[12] Insofar as data levels for all variables (bread price excepted) are modeled in natural logarithms, then shocks to, and impulse responses in, the logged variables are proportional changes in nonlogged variables, and percentage changes in the nonlogged variables when multiplied by 100. To calculate the response multiplier for a variable that generated statistically nonzero impulses in a particular impulse response simulation, one: (1) sums the statistically nonzero impulse responses into a cumulative proportional change in the respondent variable, (2) sums the corresponding impulses in the shock variable into a cumulative proportional shock variable change, and (3) then divides the respondent variable's cumulative proportional change by the shock variable's corresponding cumulative change. What results is an elasticity-like multiplier that provides what has been interpreted as history's long-run average percentage change response per percentage change in the shock variable. Unlike an elasticity, it is not defined for a particular point in time. These methods are summarized in Babula, Colling, and Gajewski (p. 380).

shock variable directionally coincided with the shock variable changes, whereas a negative multiplier suggests that a variable response was in the opposite direction of the shock.

Following Bessler, Yang, and Wongcharupan (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 some sort of an indicator of impulse significance, such as provided by the routines of Kloek and VanDijk, which have been 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 and these sets of statistically significant impulses comprise what are known as the duration times for the quarterly response patterns (see Babula and Bessler as an example). Previous research has used only impulses that were statistically nonzero when calculating the multipliers of response (Babula and Rich; RBR). Fortunately, RBR modeled the same endogenous wheat-based system as a Choleski-ordered VAR model, applied the Monte Carlo methods of Kloek and VanDijk to impulse response simulations of the two shocks examined here (a PWHEAT increase and a QWHEAT decline), and determined the sets (duration times) of statistically nonzero impulses. To calculate multipliers of response for our DAG/Bernanke VAR model's impulse response simulations, we applied the duration times (4–5 quarters) of statistically nonzero impulses that emerged from RBR's updated model to the impulse responses that emerged from simulating our DAG/Bernanke VAR model under the same two experiments.[13]

We simulated the DAG/Bernanke VAR's impulse response function in the following two ways:[14]

[13] We re-estimated the RBR Choleski VAR model with our updated sample; imposed RBR's relevant Choleski decompositions (with orderings); simulated this updated VAR model under our chosen PWHEAT and QWHEAT shocks; and applied Kloek and VanDijk's Monte Carlo methods to the simulations' impulses to discern which impulses were statistically nonzero at the 5% level. As in RBR's analysis, this updated analysis suggested that only several (here 4 to 5) of the 12 calculated impulses emerged as statistically zero and only for the same selected respondent variables: QWHEAT and PFLOUR respondent variables when a PWHEAT increase was simulated and PWHEAT and PFLOUR respondent variables when a QWHEAT decrease was simulated. These 4–5 impulses for these same respondent variables formed the 4–5-quarter duration times of statistically nonzero impulses for the impulses that emerged from the impulse response function of our DAG/Bernanke VAR simulated under the same shocks. We deemed that treating all 12 of our DAG/Bernanke VAR impulses for all respondent variables as statistically nonzero (and using all 12 to calculate multipliers) would be unrealistic and would (perhaps recklessly) disregard recent and related research done with more traditional methods and that generated overall results similar to those of our DAG/Bernanke VAR modeling analysis. So only the first 4–5 impulses for the DAG/Bernanke VAR impulse responses in the relevant respondent variables were used to calculate this paper's response multipliers. Future research efforts would do well to develop a method of discerning the statistical significance of impulse responses for Bernanke structural VAR models generally (which include a DAG/Bernanke VAR model).

[14] Throughout, we follow RBR 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 RBR, we attempted a number of other impulse response simulations, but no statistically significant responses emerged at the chosen 5% significance level. This may be due to the aggregation of the data. Shocking one of the downstream value-added wheat-based prices, say PCOOKIES or PCEREAL, uses 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. 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," with little expected influence on the five-class wheat market aggregates of PWHEAT and QWHEAT during a single market year. However, QWHEAT aggregates over the five wheat classes are the USDA's only fully and regularly published wheat data, and PWHEAT is the USDA's published price for this data. Further, shocking QWHEAT and PWHEAT makes more sense, insofar as shocks to these five-class aggregates do logically influence less aggregated wheat-based value-added markets downstream.

Table 3. Impulse Responses and Multipliers for Two Simulations: A 7% Wheat Price Increase and a 10% Wheat Quantity Decline

	Simulation 1: Wheat Price Increase		Simulation 2: Wheat Quantity Decline	
	% Change Response in			
Quarterly Step	QWHEAT	PFLOUR	PWHEAT	PFLOUR
1	0.0	+3.1	0.0	+0.0
2	−3.8	+2.5	+2.3	+0.7
3	−3.1	+1.9	+2.8	+1.1
4	−2.5	+1.4	+3.0	+1.2
5	−2.0	+1.0	+2.9	+1.3
Multiplier (unitless, nonpercentage terms)	−0.5	+0.4	−0.7	−0.3

Notes: Shocks are orthogonalized. Duration of patterns (4 to 5 quarters) are taken as those that emerged from similar simulations of the updated Rich, Babula, and Romain Choleski-ordered VAR simulated for a PWHEAT increase and a QWHEAT decline, where impulses were analyzed with Kloek and VanDijk's Monte Carlo analyses. The sign of the multiplier does not necessarily denote a positive or negative response. Rather, a positively or negatively signed multiplier indicates that the direction of the respondent variable's change is, respectively, similar to or opposite of the direction of the imposed shock.

- 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 other) reduced-form model (Babula and Rich, p. 10). Although 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 that clear the market after a full interplay of all, and often counterbalancing, demand and supply adjustments (Babula and Rich, pp. 10–11; Hamilton, ch. 11). That is, other sources could have generated 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 yield or production. The statistically nonzero impulses and the response multipliers are in Table 3.

As expected, an increase in PWHEAT induces a series of declines in wheat quantity, with these quarterly decreases declining in magnitude and lasting about a year. On average historically, each percentage rise in PWHEAT elicits a 0.5% 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 also lasted for about a year and registered, on average historically, increases of about 0.4% for each percentage rise in PWHEAT.

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 0.7% rise in wheat price. Flour price increased for about a year with the drop in QWHEAT: Increases took on a pattern of rising quarterly magnitudes and registered increases of 0.3% for each percentage drop in QWHEAT.

Analysis of Forecast Error Variance Decompositions

Analysis of decompositions of FEV is a well-known VAR innovation accounting method for discerning relations among the modeled system's time series (Bessler; Sims). Bessler (p. 111) noted that analysis of FEV decompositions is closely related to Granger causality analysis, as both tools provide evidence concerning the existence of a causal relation between 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 relation among two variables, but it also illuminates the strength and dynamic timing of such a relation (Babula and Rich, pp. 14–15; Bessler, p. 111; Saghaian, Hassan, and Reed, p. 107). Such measures are useful in applied work. Table 4 provides the FEV decompositions for the VAR model estimated above for the seven wheat-related variables. These FEV decompositions reflect the causal relations embedded in both the lagged VAR model and the chosen causal ordering among the seven variables in contemporaneous time using Bessler and Akleman's DAG/Bernanke VAR modeling methods. A variable is endogenous when large proportions of its FEV are attributed to variation of other modeled variables, and is exogenous when large proportions of its FEV are attributed to its own variation or behavior (Bessler).

Wheat price is clearly an endogenous player in the system, particularly at midterm and longer-term horizons. Own variation accounts from 66% to 80% of the PWHEAT's movements at horizons of two 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 count for as much as 41% of PWHEAT's behavior at the longer-run horizons. The impact of PFLOUR and DIFPBREAD on PWHEAT at the longer-run horizons likely reflects the downstream demand conditions. Over the long term, the demand for flour and bread products would affect 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/doughs have minor influence on PWHEAT, and this negligible influence may arise from two factors. The first involves the data aggregation issues addressed earlier: Each price may reflect classes of wheat that aggregate into only a minority share of the five-class PWHEAT "all-wheat" aggregate. And second, for wheat-based breakfast cereals, cookies/crackers, and mixes/doughs, wheat represents only a minor part of the ingredient inputs of such products. Nonwheat inputs account for significant shares of ingredient costs for these highly processed wheat-based 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 in explaining QWHEAT behavior falls steadily to about 50%. Aside from own variation, the three most important influences on QWHEAT behavior are movements in prices of important wheat-based value-added products, which collectively account for more than 40% of QWHEAT during the longer terms: own price (up to 19%); wheat flour price (15%); and bread price movements (up to nearly 13%) 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% of PFLOUR variation, but rather movements in wheat price. Wheat price's contributions to explaining flour price

Table 4. Decompositions of Forecast Error Variance Generated by the DAG/Bernanke VAR Model

Variable Explained	Horizon	% of Forecast Error Explained by						
		PWHEAT	QWHEAT	PFLOUR	PMIXES	DIFPBREAD	PCEREAL	PCOOKIES
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	19.50	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	19.01	6.78	3.80
QWHEAT	1	12.40	84.38	1.54	0.18	1.46	0.00	0.03
	2	17.37	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	2.12	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	77.20	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	7.44	62.98	9.78	0.64	0.99
DIFPBREAD	1	0.89	2.48	0.00	1.43	95.10	0.05	0.02
	2	1.42	2.87	0.04	2.51	93.00	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	88.95	0.24	1.08
	9	3.67	2.95	0.35	2.97	88.51	0.25	1.31

Table 4. (Continued)

Variable Explained	Horizon	% of Forecast Error Explained by PWHEAT	QWHEAT	PFLOUR	PMIXES	DIFPBREAD	PCEREAL	PCOOKIES
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

variation range from 75% at shorter-run horizons down to 32% at the longer-run horizons. Bread price variation accounts for more than 20% of PFLOUR variation at most horizons, whereas variation in wheat quantity explains nearly 12% of PFLOUR behavior at some longer-term horizons. Only minor proportions of PFLOUR variation may be attributable to prices of mixes/doughs, wheat-based breakfast cereals, and cookies/crackers.

As noted by Babula and Rich, 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, wheat price movement noticeably explains up to 16% of PMIXES' variation at the longer-term horizons. Although bread price variation explains up to about 10% of PMIXES, PCEREAL and PCOOKIES individually have minor influences on PMIXES' behavior. Interestingly, although 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 primarily on wheat price variation.

Bread price behavior is highly exogenous and is predominately explained by own variation, which accounts for at least 89% 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 on to 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.[15] These factors tend to minimize the impact of wheat quantity and price shocks on bread price behavior.

At all horizons, no less than 73% of PCEREAL's behavior is own variation, a high level of exogeneity potentially explained by already-proffered factors such as the importance of nonwheat ingredient inputs and the stickiness of manufactured value-added products. Interestingly, the variation in the prices of bread and of cookies/crackers collectively explain nearly 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. Bread price variation explains up to 21% of PCOOKIES' behavior, making it the most important influence on cookies/crackers price aside from own variation. As well, up to more than 15% of the 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 generate the expectation that PMIXES' variation influences the behavior of both PCOOKIES and bread price. And while PMIXES does modestly influence PCOOKIES, there is not an appreciable effect on bread price behavior. Moreover, DIFPBREAD explains up to 10% of PMIXES' behavior. 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 interesting observation. Bread price behavior accounts for at least 10%, and up to about 20%, of the variation of all endogenous variables at the longer-run horizons, with such implied patterns of causality being one way with little or no feedback 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 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 numerous and competing firms producing a homogeneous product. Additionally, bread is universally traded by more than 90% of American households, and appears to follow a random walk, thereby fulfilling Samuelson's arguments that the market may be relatively more efficient. Bread prices do not seem to return to a constant historical mean, whereas other value-added wheat-based prices do. This may imply that DIFPBREAD

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

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, the 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 analysis beyond a single market year into the longer-run timeframes. 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 wheat market events have important effects on the downstream markets over the longer horizons beyond a crop cycle. In addition, despite little or no influence suggested by the impulse response results, FEV decompositions suggest that movements in the downstream wheat-based markets have some important effects on the wheat market during the same 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 nonagricultural 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% drop for each percentage rise in PWHEAT. As well, and over a similar timeframe, flour price rises, on average, 0.4% for each percentage rise in PWHEAT. A QWHEAT decline, presumed here as quota-induced but which may also emerge from variation in production or yields, results in about a market year's worth of PWHEAT increases that, on average historically, add up to about 0.7% for each percentage drop in QWHEAT. The QWHEAT decline, over the same timeframe, also elicits a rise in PFLOUR that averages 0.3% 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.

However, the FEV decompositions extend the analysis and show a complex array of one-way and multidirectional causal influences between the wheat and wheat-using markets when analysis at time horizons 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 timeframes required to contract new factor supplies, contract new sales agreements, and to adjust preshock levels of fixed assets in response to such shocks and movements require horizons extending beyond a single market year or crop cycle.

PWHEAT, QWHEAT, and PFLOUR, as expected, share a complex web of bidirectional causal influences as seen from Table 4. 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 44% to nearly 80% of PFLOUR variation, and for no more than about 11% of PCOOKIES' variation.

Bread price movements contribute importantly to variation in all other modeled variables, including PMIXES, PFLOUR, PCEREAL, and PCOOKIES, although movements in these latter four prices have little influence on bread price behavior (Table 4). 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 more than 30% of QWHEAT variation at the longer-run horizons.

The QWHEAT and PWHEAT are the only wheat market variables for which fully detailed S&O tables are published. The downstream markets use less aggregated wheat classes: For example, cookies/crackers production uses softer wheat classes with low protein contents, whereas 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 4 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 five-class aggregates in PWHEAT or QWHEAT move? Answering such questions is beyond the limits of our reduced-form model, and hence is an area of recommended future research.

[Received May 2003; Accepted July 2003.]

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