Using Directed Acyclic Graphs and VAR Econometrics to Simulate the Upstream and Downstream Effects of Imposition of an Import Quota: An Application to U.S. Wheat-Related Markets

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__**Abstract**__: The aim of this paper is to demonstrate how a newly developed methodology, the combination of directed acyclic graph (DAG) analysis with Bernanke structural vector autoregression (VAR) methods, is used to develop a reduced form model of a commodity-based system. We simulate the model to reflect imposition of an import quota on wheat and wheat products. We use the methodology to discern the effects on U.S. markets for wheat and for wheat products from an import quota on U.S. wheat. We focus on price effects, patterns of quarterly price effects, strength of price responses (elasticity-like response multipliers), and the strength and dynamic timing of quarterly wheat and wheat products. This application may serve as a template in using new DAG/Bernanke VAR modeling tools in applications to other markets and in other countries.

This paper applies a new econometric method to a reduced form time series model of wheat market and estimates market effects of imposing wheat quota on U.S. wheat and wheat products. The model is designed to reflect the wheat trade between the U.S. and Canada, as well as the associated wheat trade policy in the two countries.

Economic theory suggests that the U.S. wheat and its downstream markets interact and influence each other (Rich, Babula, and Romain 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. 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 1980, pp. 110-111). Vector Autoregression (VAR) methods are well-equipped to address policy-relevant dynamic issues of what unfolds between pre- and post-shock equilibria. In addition, VAR econometric methods impose as few a priori theoretical restrictions as possible so as to permit the regularities in the data to reveal themselves (Bessler 1984).

The VAR methodology was developed recently and first applied to agricultural economic issues by Bessler and Akleman (1998) and Haigh and Bessler (2003). The methodology combines establishing lines of contemporaneous causality among economic variables using directed acyclic graphs or DAGs with Bernanke's (1986) well-known structural methods of vector autoregression or VAR modeling, and is hereafter denoted as the DAG/Bernanke VAR methodology. We present the methodology and its advantages over more traditional VAR modeling procedures below (for detailed derivations and summaries of VAR econometric methods see Sims (1980), Bessler (1984), Hamilton (1994, ch. 11) and Patterson (2000, ch. 14)).

Recently, Babula, Bessler, and Payne (2003, 2004) applied the reduced form DAG/Bernanke VAR methodology to a quarterly system of wheat-related markets. We adapt this model and use its results from simulation of the impulse response function and from analysis of forecast error variance or FEV decompositions to discern the dynamic effects of imposing a U.S. wheat import quota similar to that imposed on certain imports of Canadian wheat during the year ending September 11, 1995 (see Glickman and Kantor 1995; Canada-U.S. Joint Commission on Grains, 1995). The quarterly system of the seven wheat-related variables (hereafter denoted interchangeably by the parenthetical labels) is as follows:

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).

The model will provide information on the four "dynamic aspects" of how a shock in wheat market-clearing quantity of wheat influences wheat and its downstream markets: (1) direction of the responses, (2) magnitude of the responses, (3) patterns of responses, and (4) the strength of relationships

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

among wheat-related variables. This is accomplished by first specifying a traditional VAR model of the seven quarterly wheat and wheat-related variables (hereafter, the “first-stage” VAR), and then applied the procedures of Bessler and Akleman (1998) and Haigh and Bessler (2003) to the first-stage VAR to render the DAG/Bernanke VAR model of the seven wheat-related variables and their causal ordering in contemporaneous time.

We examine the results from simulating this model’s impulse response function in a way that mimics imposition of an import quota on U.S. wheat. The remainder of this paper is comprised of several sections. First, we summarize Babula, Bessler, and Payne’s (2004) quarterly VAR model of the U.S. wheat and wheat product markets. We discuss an array of specification issues, including rationale to use a VAR model and summarize a diagnostic evidence of its estimation. Second, we discuss the DAG/Bernanke VAR methodology (Bessler and Akleman (1998) and Haigh and Bessler (2003)), as applied the quarterly system of U.S. wheat and wheat product markets. We show the advantages of DAG methods in choosing an ordering of variables in contemporaneous time when confronted with several competing orderings. In the following two 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 response multipliers and to illuminate the dynamic quarterly effects on the U.S. markets for wheat and wheat products from imposing a presumably quota-induced decrease in wheat on the model’s impulse response function. A summary and conclusions follow.

The VAR Model: Specification, Data, Estimation, and Model Adequacy

The seven-equation system was estimated as a VAR model in logged levels (except for first difference in wholesale price of wheat (DIFPBREAD) because cointegration was not an issue as unit root test results suggest that six of the seven variables are likely stationary (in logged levels).

We applied Tiao and Box’s lag selection methods to the above vector of endogenous variables, and evidence suggested a one-order lag structure. In other words, first-stage VAR model is as follows:

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

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 to a variable as assigned in equation (1). The nougat-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.

Each of the seven equations included a time trend and three seasonal binary ("dummy") variables (Babula, Bessler, and Payne 2004). Three event-specific binary variables were included in each VAR equation: 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 certain Canadian durum and non-durum wheat for the year ending September 11, 1995 (Babula, Bessler, and Payne 2004).

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] Babula, Bessler, and Payne (2004) collected quarterly market year data for the seven endogenous variables and estimated the VAR model over the 1986/87:1 through 2002/2003:2 period with ordinary least squares, which Sims (1980) and Bessler (1984) established as the appropriate estimator for VAR models. The VAR model was estimated in natural logarithms so that shocks to and impulse responses in the logged variables reflect approximate proportional changes in nonlogged variables.

Hamilton (p. 324-327) summarizes how 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

[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.

quantities and prices specifically demanded or specifically supplied, but rather are prices and quantities that clear the market (Hamilton, pp. 324-327; Babula, Bessler, and Payne 2004). So a simulation's responses from a presumably quota-induced decline in QWHEAT are actually net changes after all, and sometimes countervailing, effects of supply and demand have played out (Babula, Bessler, and Payne 2004; Babula and Rich, p. 5, 2001).

Since detailed 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, we followed Babula, Bessler and Payne (2004) to model wheat and wheat product markets as reduced form price relationships (see also Babula and Rich 2001; Rich, Babula, and Romain 2002).

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 (in logged levels) were stationary (see Babula, Bessler, and Payne's (2004) for testing results and evidence which supported the choice of a VAR model (specified in equation 1) over a Johansen and Juselius (1990, 1992) VEC of the system).

Sources of Quarterly Data and Data Issues

QWHEAT, the U.S. market-clearing quantity of wheat, is the sum of beginning stocks, production, and imports, which are published by the USDA (2002, 2003).[4] Each equation's quarterly seasonal binary

[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*. Babula, Bessler, and Payne (2004) 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. 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.

[4]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 (U.S. International Trade Commission or USITC 1994, p. II.83 and appendix M; Babula and Jabara 1999 , pp. 90-91). This valuable evidence was based on highly

variables play an important role for two reasons. First, previous VAR econometric analyses on U.S. wheat-related markets have placed seasonal binaries in such equations to capture seasonal effects (USITC 1994, ch. II; Rich, Babula and Romain 2002, p. 103; and Babula and Rich 2001). And second, the seasonal binary variables capture the effects of annually-recurring, production-induced QWHEAT spike in each market year's initiating quarter (Babula and Rich 2001).

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. VAR model is adequately specified using Ljung-Box portmanteau and Dickey-Fuller tests (Babula, Bessler, and Payne (2004)).

Directed Acyclic Graphs

The above VAR modeling methods incorporates a lag structure which captures lagged causal relationships among PWHEAT, QWHEAT, PFLOUR, PMIXES, DIFPBREAD, PCEREAL, and PCOOKIES. The seven VAR variables are clearly correlated in contemporaneous time as well, although the VAR methods above do not address such contemporaneous correlation (Bessler 1984, p. 114). It is well known that ignoring causal orderings among a VAR's endogenous variables in contemporaneous

reliable 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 (Rich, Babula, and Romain 2002; Babula and Rich 2001).

time may produce impulse response simulations and FEV decompositions that may not represent observed market relationships (Sims; Bessler, p. 114; Saghaian, Hassan, and Reed, p. 104). DAG methods are an evidentially-based way of *ordering* variables in contemporaneous time.

Babula, Bessler, and Payne (2004) outlined the three principal ways which VAR econometric work has accounted for contemporaneous correlation. 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). Babula, Bessler, and Payne (2004) provided Choleski-based orderings of the same set of seven endogenous variables. The second approach is the application of Bernanke's structural VAR methods where prior notions of evidentially-based and/or theoretically-based causal orderings in contemporaneous time may be imposed on a VAR's endogenous variables (Bessler and Akleman , p. 1144). To compound the challenge of establishing a contemporaneous ordering with these two traditional VAR approaches is a factor of arbitrariness. There are several alternative and competing orderings to choose. 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. Bessler and Akleman (1998, p. 1144) noted that a potential problem with a Choleski-based approach is that the world may not be recursive, while a potential problem with Bernanke's approach is that the true contemporaneous ordering may in fact not be the optimal or most realistic choice. 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 non-orthogonalized setting. 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.

The DAG/Bernanke VAR approach offers a fourth approach that "nails-down" an evidentially supported optimal ordering from a set of competing alternatives. where The DAG analysis of Scheines et.

al. (1994) and Spirtes, Glymour, and Scheines (2000) is used to help in choosing a set of contemporaneous causal relations from a set of theoretically consistent alternatives, and then impose the evidentially-supported causal relations on a Bernanke-type structural VAR (see Babula, Bessler, and Payne (2004), Bessler and Akleman (1998) and Haigh, and Bessler (2003)). By engaging statistical evidence, this approach may avoid excessive reliance on recursive restrictions, expert opinions, and/or arbitrariness of choice in selecting among competing, yet theoretically consistent, contemporaneous orderings when using more traditional VAR modeling procedures (Babula, Bessler, and Payne 2004).

We applied the TETRADII PC algorithm to construct a DAG on innovations from their first-stage VAR model (DAG applications follow the theoretical work of Pearl (1995) and the TETRAD algorithms described in Spirtes, Glymour, and Scheines (2000). The PC algorithm begins with a general unrestricted set of relationships among the variables (errors from each VAR equation) and proceeds stepwise to remove *edges* between variables and to *direct* causal flow. Edges between variables are removed sequentially based on zero correlations or partial (conditional) correlations.

DAG Applications to Wheat and Wheat Products Markets

In sorting out how the seven wheat endogenous variables are ordered in contemporaneous time we follow Babula, Bessler, and Payne's (2004), Bessler and Akleman (1998), and Haigh and Bessler (2003). 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 among the seven variables. Panel B provides the edges that our analysis 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, we analyze unconditional correlations, eliminates all statistically zero edges, and retains all statistically nonzero correlations (see Scheines et. al. 1994; Spirtes, Glymour, and Scheines 2000). Second, we further analyze all remaining conditional correlations for eliminating such conditional correlations that are statistically zero, and retaining the statistically nonzero ones. Panel B in figure 1 provides the edges retained in these two stages. This figure indicates that some edges are directed, and some are undirected, giving rise to several competing systems of observationally equivalent contemporaneous causality relationships. Haigh and Bessler (2003) developed a method to optimally choose among such competing systems of ordered relations: 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) was imposed on the DAG/Bernanke model.

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 our 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; Bessler and Akleman, p. 1146).

Table 1 provides the essentials for stages 1 and 2 (see also Babula, Bessler, and Payne's application of the analysis for more details). The correlation matrix (lower triangular innovation correlation matrix) was generated by the OLS-estimated VAR model. Each of the elements is correlation coefficient 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 correlation coefficients 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 relationship where wheat price influences or causes flour price. Recall that rho(1,3) = +0.92 with a p-value of about zero.

- PCEREAL(Y6) → 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.

- 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. 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(7,4) of +0.22 has a 0.08 p-value. This edge also has two observationally equivalent possibilities: Y7→ Y4 or Y4→ Y7.

• QWHEAT (Y2) is exogenous.

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 must 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. 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.

Schwarz's loss metric modified and adapted by Haigh and Bessler (2003) 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 (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. 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 Impulse Responses and FEV Decompositions to Discern Effects of a U.S. Wheat Import Quota

The impulse response function is well-known for its usefulness in simulating, over time, the effect of a shock in one of the system's series on itself and on other series in the system (Bessler 1984; Hamilton 1994, ch. 11). Such is accomplished by converting the VAR model into its moving average (MA) representation, the parameters of which are complex combinations of the VAR regression coefficients (Bessler 1984; Hamilton 1994, ch. 11). 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 and McKenzie). More specifically, examination of the impulse response patterns simulated under a decline in QWHEAT, as explained below, can illuminate the dynamic nature and patterns of quarterly responses of the VAR model's endogenous variables when a U.S. import quota on wheat is imposed.

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). 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 shock variable directionally coincided with the shock variable changes, while a negative multiplier suggests that a variable response was in the opposite direction of the shock (readers interested in multiplier calculation methods are refereed to Babula, Bessler, and Payne (2004)).

Following Bessler, Yang, and Wongcharupan (2002, p. 819), Babula, Bessler, and Payne (2004) did not calculate confidence intervals on the impulse response functions. Although not a difficult task for a VAR ordered with a Choleski decomposition, calculating standard errors of impulse response functions for a Bernanke structural VAR was beyond the scope of this paper, 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 (here 12) 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 1987 as an example). Previous research has used only impulses, which were statistically nonzero when calculating the multipliers of response (Rich, Babula, and Romain 2002; Babula and Rich 2001). Fortunately, Rich, Babula, and Romain (2002) 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 a presumably quota-induced QWHEAT decline, and determined the sets (duration times) of statistically nonzero impulses. And further, the results from these two articles were very similar. 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 (see Babula, Bessler, and Payne (2004)'s updated work of the Rich, Babula, and Romain (2002)) to the impulse responses which emerged from simulating our DAG/Bernanke VAR model under a similar QWHEAT-shock experiment.

We imposed a presumably quota-induced QWHEAT decline on the reduced form DAG/Bernanke VAR model and examined the dynamic aspects of quarterly response patterns in PWHEAT, PFLOUR, PMIXES, PCEREAL, and PCOOKIES.[5] Given the reduced form nature of the DAG/Bernanke VAR model, there is some subjective leeway in identifying the source of QWHEAT decrease imposed as the model's shock (Babula, Bessler, and Payne 2004; Babula and Rich, 2001, p. 10). While the quota-induced nature of the QWHEAT shock is valid and accepted in recent literature, the shock could have

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[5] The size of the decline imposed and simulated was an orthogonalized standard error decrease of 9.7 percent. Yet it is well known from previous research that such VAR models as ours is linear, and given this linearity, the size of the shock is irrelevant. For example, by the model's linearity, once can characterize the effects of a 20 percent QWHEAT shock by simply multiplying the impulse response results from a 10 percent shock by the scaler 2.0. Likewise, one can characterize the effects of a 10 percent increase by simply taking the impulse response results from a 10 percent QWHEAT decline and multiplying the results by -1.0. The linear model provides the same multiplier regardless of shock size and shock sign. See Babula, Colling, and Gajewski (1994, p. 377). As well, we followed Babula, Bessler, and Payne (2004) and Rich, Babula, and Romain (2002) and do not analyze the dynamic attributes of DIFPBREAD response. 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.

arisen from other sources -- perhaps a decline in yield on the supply side or a decline in demand -- since the DAG/Bernanke VAR model's estimated reduced-form relations quantity (QWHEAT) is neither quantity specifically supplied or demanded, but rather the quantity that clears the market after a full interplay of all, and often counterbalancing, demand and supply adjustments (Hamilton 1994, ch. 11; Babula, Bessler, and Payne 2004; and Babula and Rich 2001, pp. 10-11). So other sources could have generated the same shock.

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 percent 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 percent for each percentage drop in QWHEAT. The impulse response results suggest that the fall in QWHEAT would have little effect further downstream beyond the flour market, and effects would be confined to a the approximate time frame of a single crop cycle or market year. Yet Doan (1996, p. 8.13) strongly cautions against use of impulse response analysis alone, and suggests an accompanying analysis of FEV decompositions provided below.

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; Bessler). Bessler (p. 111) noted that analysis of FEV decompositions is closely related to Granger causality analysis: not only do FEV decompositions suggest the simple existence of a causal relationship among two variables as does Granger causality analysis, but FEV decompositions go further and provide insight on the dynamic timing of such a relationship (Babula, Bessler, and Payne 2004; Babula and Rich 2001). 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, Bessler, and Payne 2004; Babula and Rich, 2001, pp. 14-15; Saghaian, Hassan, and Reed, p. 107). Table 3 provides the FEV decompositions generated model for the seven wheat-related variables (see also Babula, Bessler, and Payne's (2004)). 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).

Babula, Bessler, and Payne (2004) provide an exhaustive analysis of these FEV decomposition results, which we do not replicate here: we refer interested readers to their article. We limit focus here on the FEV decomposition patterns relevant to the imposition of an import quota on U.S wheat. More specifically, we focus on how QWHEAT changes reflective of a wheat import quota's imposition, and subsequent PWHEAT movements, influence each other as well as the downstream wheat-related value added prices. Other results are mentioned when of interest.

Given that wheat production is climatically driven, and that part of QWHEAT is produced in the Canadian market, it is no surprise that wheat quantity is highly exogenous, here at the shorter run horizon. At horizons of four quarters or less, from 61 percent to 84 percent of QWHEAT behavior is explained by own-variation. As the time horizon lengthens, QWHEAT becomes more endogenous where own-variation explains only about half of its variation. The second most important factor of QWHEAT variation is PWHEAT, which explains up to 19 percent of QWHEAT behavior. Wheat and flour prices collectively explain from 30 to 32 percent of QWHEAT variations at the longer run horizons. As well, bread price variation accounts for up to 13 percent of QWHEAT behavior.

Wheat price has exogeneity patterns similar to those of QWHEAT: the price is highly exogenous at shorter run horizons, where own-variation explains up to 80 percent of its behavior. This exogeneity declines at longer run horizons, with own-variation accounting for about a third of its behavior.

QWHEAT and PWHEAT movements collectively explain the preponderance of the variation in both variables: up to 97 percent of QWHEAT and up to 87 percent of PWHEAT. Such clearly suggests that QWHEAT and PWHEAT are heavily dependent on each other, and that a QWHEAT decline from a quota would elicit a response in wheat price as well.

FEV decompositions in table 3 coincide with impulse response results, and suggest that flour price is heavily influenced by QWHEAT changes (perhaps from a quota) and from any subsequent movements in wheat price elicited by the QWHEAT changes. PFLOUR is highly endogenous, with no more than about 21 percent of its behavior explained by own-variation. A quota-induced fall in QWHEAT and any ensuing changes in PWHEAT would collectively explain up to nearly 80 percent of flour price behavior at horizons of 1-2 quarters, and from 44 to 56 percent of flour price behavior at horizons beyond two quarters. Movement of bread price explain a noticeable 21-22 percent of flour price variation at horizons beyond two quarters. Generally speaking, FEV decompositions and impulse response results suggest that shocks in QWHEAT, perhaps quota-induced, and subsequent changes in wheat price heavily impact the wheat flour market downstream.

Recent VAR econometric research on U.S. wheat-related markets conclude that the importance of wheat market shocks (changes in QWHEAT and PWHEAT) lessens as the level of downstream processing for a wheat-related, value-added market rises (Babula, Bessler, and Payne 1994; Babula and Rich 1981). Wheat-related production costs take on decreasing shares of production costs as the level of processing rises: for example, FEV decompositions suggest that QWHEAT and PWHEAT movements collectively explain from 43 percent to 80 percent of PFLOUR variation, and for no more than about 11 percent of PCOOKIES variation. So a quota-induced fall in QWHEAT and subsequent changes in wheat price are expected to have generally lessened market effects the further one proceeds downstream from the wheat farm gate.

Beyond the flour market, FEV decompositions in table 3 support impulse response results and suggest that a quota-induced change in QWHEAT, and any elicited PWHEAT changes, are likely to have, at most, moderate influences on wheat-related prices. Presumably quota-induced changes in both wheat market variables account for no more than about 18 percent of PMIXES behavior; no more than about 11 percent of PCOOKIES behavior; and negligible proportions of the variation in DIFPBREAD. And what influence that the presumably quota-induced wheat market changes do have on the downstream mixes/doughs and cookies/crackers markets occur at the longer run horizons beyond a single market year or crop cycle (4-5 quarters). Perhaps such longer horizons are required for downstream market agents to alter long term contracts (purchases/sales) and to adjust fixed capital investment levels (Babula, Bessler, and Payne 2004). Note that these longer run downstream effects on these two markets did not emerge from the impulse response results.

Also of note is that beyond the flour market, variation in bread price does noticeably influence prices of wheat-related and value-added products. Bread price movements account for up to more than 10 percent of the variation in the prices of mixes/doughs, wheat-based breakfast cereals, and cookies/crackers. In fact, table 3 suggests that bread price variation contributes noticeably to the explanation of the behavior of all seven VAR variables, with little feedback from the other six variables to the explanation of bread price variation (for more details, see Babula, Bessler, and Payne (2004)). Bread price was the only variable that generated clear evidence of a unit root. This may imply that bread price is an efficient price where there is no appreciable predictability of its behavior from its past, as with any random walk, and where the best prediction is its current value. The bread market, compared with the other represented markets, appeared very competitive with its homogenous product (represented by the chosen PPI), the large number of U.S. bread producers, and with its near-universal product consumption by more than 90 percent of American households (Babula, Bessler, and Payne 1994). This may fulfill Samuelson's (1965) arguments that the bread market may be relatively more efficient than the wheat-based markets represented in the DAG/Bernanke VAR model; that as an efficient price, bread prices do not return to a constant historical mean, while other wheat-related prices do; and that bread price may constitute a widely-watched "informational" variable upon which the grain-based foods industry base decisions (Babula, Bessler, and Payne 2004). That is, Babula, Bessler, and Payne (2004) argued that producers of the less competitively structured markets for other wheat-based, value-added markets may look to bread price behavior for guidance in administering their other wheat-based value-added product prices – an argument which they admit is conjectural and would constitute a productive area of future research.

Summary and Conclusions

We analyzed DAG/Bernanke VAR model's impulse response function and forecast error variance (FEV) decompositions in order to discern the market impacts of imposing a U.S. import quota on wheat and wheat products, resembling that imposed on certain U.S. imports of Canadian wheat during the year ending September 11, 1995.

The impulse response function of the reduced-form DAG/Bernanke VAR model was simulated for a presumably quota-induced decline in the available quantity of wheat. Results suggest that on average historically, each percent decline in wheat quantity would elicit a 0.7 percent rise in wheat price and a 0.3 percent rise in flour price over the period of about a single market year, without having much of an effect on the markets further downstream.

Analysis of FEV decompositions, combined with the impulse response results, suggested that a presumably quota-induced fall in wheat demand and supplies would elicit an ensuing change in wheat price, and movements in both of these wheat market variables would in turn have certain effects on downstream markets. As with the impulse response results, the FEV decompositions suggest that a quota-induced wheat market shocks will appreciably affect flour price, although these FEV results suggest that such price of flour (PFLOUR) influence would extend beyond the time frame of a single market year suggested by the impulse results. And while impulse response results suggested that a quota -induced decline in QWHEAT would have little or no downstream effects beyond the wheat flour market, FEV decompositions suggested that there would be some effects on the mixes/doughs and cookies/crackers markets, and generally at longer term horizons beyond a single market year.

As with Babula, Bessler, and Payne, we also encountered evidence that suggested a one-way causal relationship from bread price movements to all six other endogenous variables with little or no causal feedback from these six variables to bread price behavior. Combined with other econometric evidence cited above, these results suggest that the bread market may be more competitive and perhaps more efficient than the other markets in the VAR model, and that bread price may serve as a "flagship" or "informational" variable upon which the agents from other less efficient and less competitive wheat-related markets may base business decisions.

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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

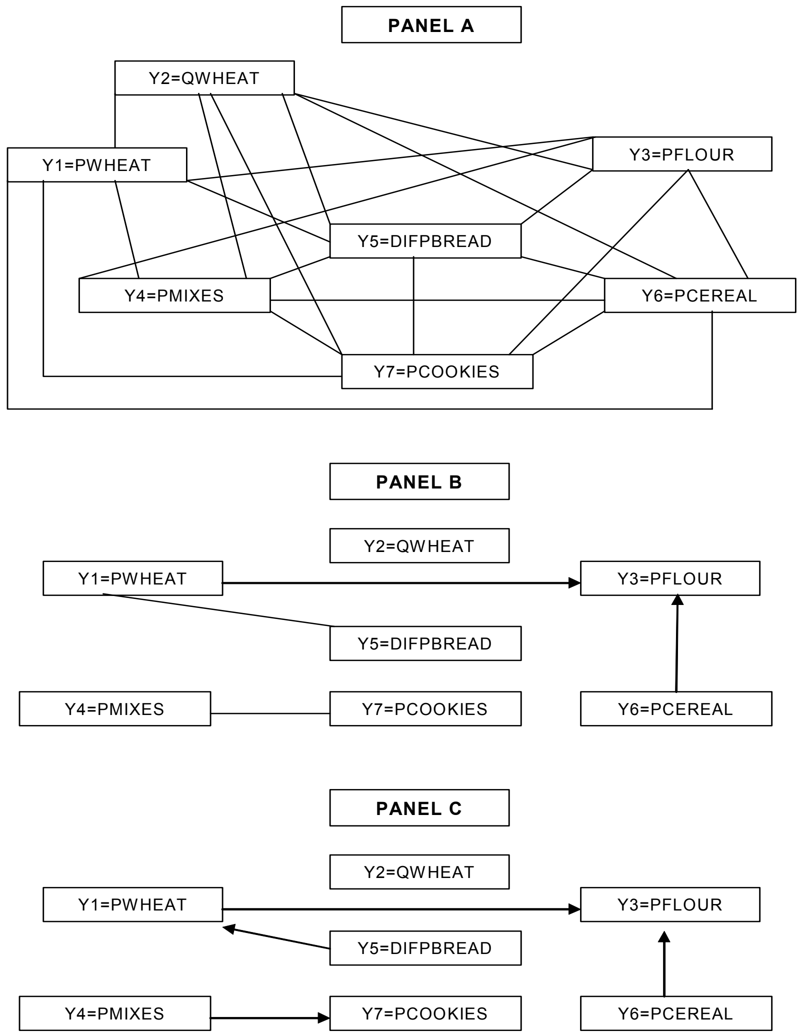

Table 1
VAR Model's Correlation and Covariance Matrices and Correlation P-Values in Lower-Triangular Form Correlation and Covariance Matrix

Product Combinations	Correlation Coefficient	P-Values	Salvaged Edges* (10% significance level)
Y1*Y2	-0.44	0.0002	
Y1*Y3	0.92	0.0000	PRICE OF WHEAT → PRICE OF FLOUR
Y1*Y4	-0.05	0.7100	
Y1*Y5	0.23	0.0610	PRICE OF WHEAT — DIFPBREAD
Y1*Y6	0.10	0.4210	
Y1*Y7	-0.08	0.5120	
Y2*Y3	-0.42	0.0003	
Y2*Y4	0.09	0.4760	
Y2*Y5	0.02	0.8600	
Y2*Y6	-0.08	0.5200	
Y2*Y7	-0.06	0.6340	
Y3*Y4	-0.10	0.4130	
Y3*Y5	0.16	0.2130	
Y3*Y6	0.21	0.0580	PRICE OF CEREAL → PRICE OF FLOUR
Y3*Y7	-0.13	0.2990	
Y4*Y5	-0.05	0.6680	
Y4*Y6	-0.03	0.8290	
Y4*Y7	0.22	0.0800	PRICE OF MIXES — PRICE OF COOKIES
Y5*Y6	-0.15	0.2280	
Y5*Y7	-0.03	0.7840	
Y6*Y7	-0.14	0.2710	
			QWHEAT or Y2 = exogenous

*WHAT IS SALVAGED EDGES ….

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 a 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.

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

Variable explained	Horizon	PWHEAT	QWHEAT	PFLOUR	PMIXES	DIFPBREAD	PCEREAL	PCOOKIES
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