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# PRICE DYNAMICS IN THE INTERNATIONAL WHEAT MARKET: MODELING WITH ERROR CORRECTION AND DIRECTED ACYCLIC GRAPHS*

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**ABSTRACT.** In this paper we examine dynamic relationships among wheat prices from five countries for the years 1981–1999. Error correction models and directed acyclic graphs are employed with observational data to sort-out the dynamic causal relationships among prices from major wheat producing regions: Canada, the European Union, Argentina, Australia, and the United States. An ambiguity related to the cyclic or acyclic flow of information between Canada and Australia is uncovered. We condition our analysis on the assumption that information flow is acyclic. The empirical results show that Canada and the U.S. are leaders in the pricing of wheat in these markets. The U.S. has a significant effect on three markets excluding Canada.

## 1. INTRODUCTION

Issues of market power, government intervention, and price instability have been interwoven in international grain markets. Policymakers, economists, and farmers have periodically raised concerns over the competitiveness of international grain trade. This may be attributable to the fact that a small number of international grain exporters handle the majority of grain exports (Patterson and Abbott, 1994). Wheat is among the most important internationally traded grain commodities, and the perception of imperfect competition and price discrimination in the international wheat market has received

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much attention recently.[1] This perception is reinforced by the facts that the world wheat market is characterized by a limited number of major exporting regions and that state trading seems to be more the rule than the exception. Five regions—the United States (U.S.), Canada, Australia, the European Union (E.U.), and Argentina, account for more than 80 percent of total exports of wheat (Mohanty, Peterson, and Kruse, 1995; Mohanty, Meyers, and Smith, 1999). In Canada and Australia, a single state trading enterprise (the Canadian and Australian Wheat Boards, respectively) exercises all wheat marketing and export practices for that country (Schmitz and Gray, 2000). The Canadian Wheat Board (CWB) is the largest state trading enterprise, both in terms of volume and annual sales, reporting to the World Trade Organization. There is much concern that state trading enterprises such as the CWB and the Australian Wheat Board (AWB) may significantly distort trades by exercising price discrimination (Carter and Wilson, 1997; Mohanty, Meyers, and Smith, 1999; Schmitz and Gray, 2000).

To shed light on the possible discriminating price behavior, many studies have explored causal relationships among prices in the international wheat market. Using internal wheat market prices, Spriggs, Kaylen, and Bessler (1982) and Gilmour and Fawcett (1987) did not find evidence of significant price leadership between the U.S. and Canada. More recent studies have included other major exporters such as Australia, Argentina, and the E.U. Using wheat export prices, Goodwin and Schroeder (1991) and Mohanty, Peterson, and Kruse (1995) found that the U.S. tends to have a strong influence on the prices of other major exporters. Mohanty, Peterson, and Smith (1996) found that the U.S. wheat price is influenced by the Canadian price in the long run, although the reverse does not hold. By contrast, Mohanty, Meyers, and Smith (1999) concluded that there is no distinctive price leadership among the five major wheat exporters. Clearly, the empirical results are mixed and should be subject to further analysis.

This study models international wheat price dynamics by combining directed graphs and error correction modeling. Applications of the directed graphs in economics are not common. With the use of directed graphs (as in Spirtes, Glymour, and Scheines, 1993; Pearl, 1995; Pearl 2000; Swanson and Granger, 1997), the study contributes to the literature in two ways. First, this study is able to shed more light on contemporaneous causal relationships among multiple markets with strong contemporaneous correlations. Goodwin and Schroeder (1991, p. 242) document strong contemporaneous correlations of various wheat market innovations (e.g., the residuals from a vector autoregression (VAR)

[1]The U.S. General Accounting Office recently released two major reports (1996 and 1998) that are directly related to imperfect competition in the international wheat market possibly caused by state trading enterprises such as the CWB and the AWB, see Schmitz and Gray (2000). The U.S. International Trade Commission also conducted several investigations on the ability of price discrimination by the CWB in the 1990s. See the United States International Trade Commission (2001) for a most recent discussion of this issue.

system) and point out the importance of this phenomenon in understanding price adjustment across markets. More generally, Uri and Rifkin (1985) emphasize the importance of such strong contemporaneous correlations in defining a geographic market. This study extends previous work by providing more insight into directions of instantaneous causal flows based on contemporaneous correlations. Second, the ability to identify directions of instantaneous causal flows further advances VAR innovation accounting analysis. Determining the directions of contemporaneous causal flows among price innovations is not only important itself, but is also crucial to VAR-type innovation accounting because it may suggest a data-determined pattern for the structural decomposition of VAR residuals (Swanson and Granger, 1997; Bessler and Yang, 2003). This paper is organized as follows: Section 2 briefly reviews the theory of directed acyclic graphs; Section 3 describes the data and some institutional background; Section 4 presents empirical analysis and findings; and Section 5 provides conclusions.

## 2. DIRECTED ACYCLIC GRAPHS

As is well known, Granger (1969) causality exploits the fact that a cause precedes its associated effect, whereas an effect does not precede its cause. More recently, Spirtes, Glymour, and Scheines (1993) and Pearl (1995, 2000) describe a nontime sequence asymmetry in causal relations, which may be as helpful as Granger's time sequence asymmetry in causal systems.[2] For three variables $X$, $Y$, and $Z$ we may have such relations that $X$ causes $Y$ and $Z$, illustrated as $Y \leftarrow X \rightarrow Z$. This immediately suggests that the unconditional association between Y and Z is nonzero but the conditional association between $Y$, and $Z$, given knowledge of the common cause $X$, is zero. Thus, common causes screen off associations between their joint effects. On the other hand, if we have such relations that both $X$ and $Z$ cause $Y$, illustrated as $X \rightarrow Y \leftarrow Z$, then the unconditional association between $X$ and $Z$ is zero. However, the conditional association between $X$ and $Z$, given the common effect $Y$, is not zero. Thus, common effects do not screen off association between their joint causes. These "screening-off" phenomena have been built into a rather expansive literature of directed acyclic graphs.

Essentially, a directed graph is an illustration using arrows and vertices for representing the causal flow among a set of variables. A graph is an ordered triple (**V**, **M**, **E**) where **V** is a nonempty set of vertices (variables), **M** is a nonempty set of marks (symbols attached to the end of undirected edges), and **E** is a set of ordered pairs. Each member of **E** is called an edge. Vertices connected by an edge are said to be adjacent. If we have a set of vertices $\{A, B, C, D, E, F, G, H\}$: (i) the undirected graph contains only undirected edges (e.g., $A$—$B$); (ii) a directed graph contains only directed edges (e.g., $B \rightarrow C$);

[2]Several authors have described such asymmetries. A partial list includes Papineau (1985), Simon (1953), and Orcutt (1952). The reader is directed to Hausman (1998) for a recent description of causal asymmetries.

(iii) an inducing path graph contains both directed edges and bidirected edges ($C \leftrightarrow D$); and (iv) a partially oriented inducing path graph contains directed edges ($D \rightarrow E$), bidirected edges ($E \leftrightarrow F$), nondirected edges ($F_o$—$_oG$), and partially directed edges ($G_o \rightarrow H$). A directed acyclic graph is a directed graph that contains no directed cyclic paths. An acyclic graph has no path that leads away from a variable only to return to that same variable. The path $A \rightarrow B \rightarrow C \rightarrow A$ is labeled *cyclic* as here we move from $A$ to $B$, but then return to $A$ by way of $C$. Only acyclic graphs are used in the paper.

Directed acyclic graphs are illustrations representing conditional independence as given by the recursive decomposition

$$\Pr(v_1, v_2, v_3, \ldots, v_n) = \prod_{i=1}^{n} \Pr(v_i \,|\, pa_i)$$

where Pr is the probability of vertices (variables) $v_1$, $v_2$, $v_3, \ldots, v_n$ and $pa_i$ the realization of some subset of the variables that precede (come before in a causal sense) $v_i$ in order ($v_1$, $v_2$, $v_3, \ldots, v_n$), and the symbol $\Pi$ represents the product operation, with index of operation denoted below (start) and above (finish) the symbol. Pearl (1995) proposes d-separation (direction separation) as a graphical characterization of conditional independence. That is, d-separation characterizes the conditional independence relations given by the above product ($\Pi$Pr). If we formulate a directed acyclic graph in which the variables corresponding to $pa_i$ are represented as the parents (direct causes) of $v_i$, then the independencies implied by the product given above can be read off the graph using the notion of d-separation as defined by Pearl (1995):

> Definition: "Let $X$, $Y$, and $Z$ be three disjoint subsets of vertices (variables) in a directed acylic graph $G$, and let $p$ be any path between a vertex (variable) in $X$ and a vertex (variable) in $Y$, where by 'path' we mean any succession of edges, regardless of their directions. $Z$ is said to block $p$ if there is a vertex $w$ on $p$ satisfying one of the following: (i) $w$ has converging arrows along $p$, and neither $w$ nor any of its descendants are on $Z$, or, (ii) $w$ does not have converging arrows along $p$, and $w$ is in $Z$. Further, $Z$ is said to d-separate $X$ from $Y$ on graph $G$, written $(X \perp Y | Z)_G$, if and only if $Z$ blocks every path from a vertex (variable) in $X$ to a vertex (variable) in $Y$" (Pearl, 1995, p. 671).

Geiger, Verma, and Pearl (1990) show that there is a one-to-one correspondence between the set of conditional independencies $X \perp Y | Z$ implied by the above factorization and the set of triples $X$, $Y$, $Z$ that satisfy the d-separation criterion in a graph $G$. If $G$ is a directed acyclic graph with vertex set $\mathbf{V}$, if $A$ and $B$ are in $\mathbf{V}$ and if $H$ is also in $\mathbf{V}$, then $G$ linearly implies the correlation between $A$ and $B$ conditional on $H$ is zero, if and only if $A$ and $B$ are d-separated given H.

The notion of d-separation can be illustrated further. Consider three variables (vertices): $A$, $B$, and $C$. A variable is a *collider* if arrows converge on it: $A \rightarrow B \leftarrow C$. The vertex $B$ is a collider, $A$ and $C$ are d-separated, given the null set. However, if we condition on $B$, we open-up the information flow from $A$ to $C$. Conditioning on $B$ makes $A$ and $C$ d-connected (directionally connected). Further, we amend the graph given above to include variable $D$, as a child of $B$, such that

$$\begin{array}{c} A \rightarrow B \leftarrow C \\ \downarrow \\ D \end{array}$$

If we condition on $D$ rather than $B$, we open up the flow between $A$ and $C$ also (Pearl, 2000, p. 17). This illustrates component (i) of the definition given above.

If converging arrows do not characterize our information flow, as illustrated above, but rather, if information flow is characterized by diverging arrows, then the d-separation condition is different. This is given by component (ii) of the definition above. Say we have three vertices $K$, $L$, and $M$, described by the graph: $K \leftarrow L \rightarrow M$. Here $L$ is a common cause of $K$ and $M$. The unconditional association (correlation) between $K$ and $M$ will be nonzero because they have a common cause $L$. If we condition on $L$ (know the value of $L$), the association between $K$ and $M$ disappears (Pearl, 2000, p. 17). Conditioning on common causes blocks the flow of information between common effects. In an unconditional sense, $K$ and $M$ are d-connected because they have a common cause; whereas conditioning on $L$, variables $K$ and $M$ are d-separated.

Finally, if the causal path is one of a chain (causal chain), condition (ii) in the above definition again applies. If $D$ causes $E$ and $E$ causes $F$, we have the representational flow: $D \rightarrow E \rightarrow F$. The unconditional association (correlation) between $D$ and $F$ will be nonzero, but the association (correlation) between $D$ and $F$ conditional on $E$ will be zero. For causal chains, the end points ($D$ and $F$) are not d-separated, whereas conditioning on the middle vertex $E$ makes the end points d-separated (Pearl, 2000).

Spirtes, Glymour, and Scheines (1993) have incorporated the notion of d-separation into an algorithm (PC Algorithm) for building directed acyclic graphs, using the notion of *sepset* (defined below). The PC algorithm is an ordered set of commands that begins with a general unrestricted set of relationships among variables and using a step-wise procedure removes edges between variables and directs "causal flow." The algorithm is described in detail in Spirtes, Glymour, and Scheines (1993, p. 117). More advanced versions (refinements) are described as the Modified PC Algorithm (Spirtes, Glymour, and Scheines, 1993, p. 166), the Causal Inference Algorithm (p. 183), and the Fast Causal Inference Algorithm (p. 188). We restrict our discussion to the PC algorithm because it is the most basic and easily understood version of their contribution (in our opinion).

Briefly, when applying the PC algorithm, one starts with forming a complete undirected graph $G$ on the vertex set $\mathbf{V}$. The complete undirected graph shows an undirected edge between every variable of the system (every variable in $\mathbf{V}$). Edges between variables are removed sequentially based on zero correlation or partial correlation (conditional correlation). Fisher's $z$ is used to test whether conditional correlations are significantly different from zero, where $z[\rho(i, j|k)n] = 1/2(n - |k| - 3)^{1/2} \times \ln\{[|1 + \rho(i, j|k)|] \times [|1 - \rho(i, j|k)|]^{-1}\}$ and $n$ is the number of observations used to estimate the correlations, $\rho(i, j|k)$ is the population correlation between series $i$ and $j$ conditional on series $k$ (removing the influence of series $k$ on each $i$ and $j$), and $|k|$ is the number of variables in $k$ (that we condition on). If $i$, $j$, and $k$ are normally distributed and $r(i, j|k)$ is the sample conditional correlation of $i$ and $j$ given $k$, then the distribution of $z[\rho(i, j|k)n] - z[r(i, j|k)n]$ is standard normal.

The remaining edges are then directed by using the notion of sepset, which is defined as: *The conditioning variable(s) on removed edges between two variables is called the sepset of the variables whose edge has been removed (for vanishing zero order conditioning information the sepset is the empty set).* To illustrate, 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. Direct edges between triples: $X$—$Y$—$Z$ as $X \rightarrow Y \leftarrow Z$ if $Y$ is not in the sepset of $X$ and $Z$. If $X \rightarrow Y$, $Y$ and $Z$ are adjacent, $X$ and $Z$ are not adjacent, and there is no arrowhead at $Y$, then orient $Y$—$Z$ as $Y \rightarrow Z$. If there is a directed path from $X$ to $Y$, and an edge between $X$ and $Y$, then direct ($X$—$Y$) as: $X \rightarrow Y$.

Spirtes et al. (1999) show the connection between directed graphs and the counterfactual random variable model (the random assignment experimental model) of Holland (1986). First, one needs to have a *causally sufficient* set of variables. This means that there is (are) no omitted variable(s) that in fact causes (cause) any two of the included variables under study. If variable $X$ causes both $Y$ and $Z$ and $X$ is omitted from the analysis, then an apparent causal flow from $Y$ to $Z$ (or vice versa) may be due to the fact that $X$ causes both $Y$ and $Z$, so the causal flow identified as running from $Y$ to $Z$ would be spurious (Suppes, 1970). Second, one needs to be constrained to causal flows that respect a *causal Markov condition*. That is to say, if $X$ causes $Y$ and $Y$ causes $Z$, we can factor the underlying probability distribution on $X$, $Y$, and $Z$ as $\Pr(X, Y, Z) = \Pr(X)\Pr(Y|X)\Pr(Z|Y)$. In other words, the causal flow that we attempt to uncover must respect the genealogy condition that one need only condition on its parents in order to fully capture the probability distribution generating any variable. One need not condition on grandparents, uncles or aunts, or siblings. (Here $A$ is a parent of $B$ if $A \rightarrow B$; $A$ is a grandparent of $C$ in the causal chain $A \rightarrow B \rightarrow C$; $D$ is a sibling of $C$ if $B \rightarrow C$ and $B \rightarrow D$ and no causal flow between $C$ and $D$ exists. The variable $C$ is an uncle of $E$ if $B \rightarrow C$ and $B \rightarrow D$ and $D \rightarrow E$.) The third requirement for correspondence between the PC algorithm and the randomized experiment is that the probabilities Pr that we attempt to capture by graph G are *faithful* to G if $X$ and $Y$ are dependent if and only if there is an edge between $X$ and $Y$.

The causal sufficiency, Markov, and faithfulness conditions can be violated. Thus, any result based on observational data must be viewed with caution. The causal sufficiency condition suggests that one must find a sufficiently rich set of theoretically relevant variables upon which to conduct an analysis. Failure to

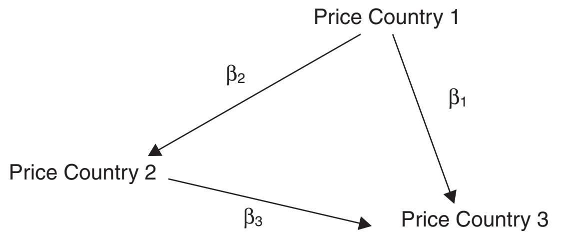


FIGURE 1: Hypothetical Causal Pattern to Illustrate Faithfulness.

include a relevant variable may lead one to put an edge between two variables when in fact both are effects of an omitted third variable. Failure of the Markov condition has been noted in quantum mechanical experiments (see Spirtes, Glymour, and Scheines, 1993). Failure to require the condition would lead us to ignore statistical dependency even in experimental designs (Spirtes, Glymour, and Scheines, 1993, p. 64). Finally, the faithfulness condition can be violated if parameters between causes happen to be of the correct magnitude to cancel one another. Scheines et al. (1999, p. 181) illustrate a violation of the faithfulness condition as shown in Figure 1. Here we write the parameter value connecting prices from three different countries using the letters $\beta_1$, $\beta_2$, and $\beta_3$.

If $\beta_1 = -(\beta_3\beta_2)$, then the variables Price in Country 1 and Price in Country 3 are uncorrelated. Thus, we will fail to place an edge between Price Country 1 and Price Country 3, even though the true model requires one. The exact off-setting of parameter values in the true population, while possible, seems unlikely. The faithfulness assumption says that if zero correlations are observed, it is because the edge is not present and not because of canceling of deep parameters from the underlying structural model. (Theorists tell us that such cancelations can arise, as we demonstrated through a constructed example; whether or not such an example can be found in real world data is another matter. It seems to us that demonstration of such requires either a random assignment experiment or a priori knowledge of the true model).

Below we apply the PC algorithm. It sits firmly on causal sufficiency, the causal Markov property, and the faithfulness condition. Our recommendation related to any result obtained from this application is that results should be interpreted with caution because violations of each of these conditions are possible. However, short of actually conducting a random assignment experiment, the methods applied below appear to be appropriate for assigning causal flow to observational data.

## 3. DATA AND BACKGROUND

The data used for analysis are monthly free on board (FOB) export price quotations for the period from January 1981 to June 1999. The measurement unit is U.S. dollars per ton. Specifically, the price series include: U.S. #2 hard red winter, ordinary protein, and gulf; Canadian #1 western red spring, 13.5 percent, and St. Lawrence; Australian standard wheat; the European standard wheat (Rouen); and Argentina trigo pan wheat. The price data are similar to those used in recent studies of price relationships in the international wheat market (Goodwin and Schroeder, 1991; Mohanty, Peterson and Kruse, 1995; Mohanty, Meyers, and Smith, 1999). The data sources are various issues of *World Wheat Statistics* and *World Grain Statistics*, published by the International Wheat Council.

Plots of our data are given in Figure 2. Notice that for all five markets, prices decline throughout much of the 1980s, reaching a trough in late 1987.

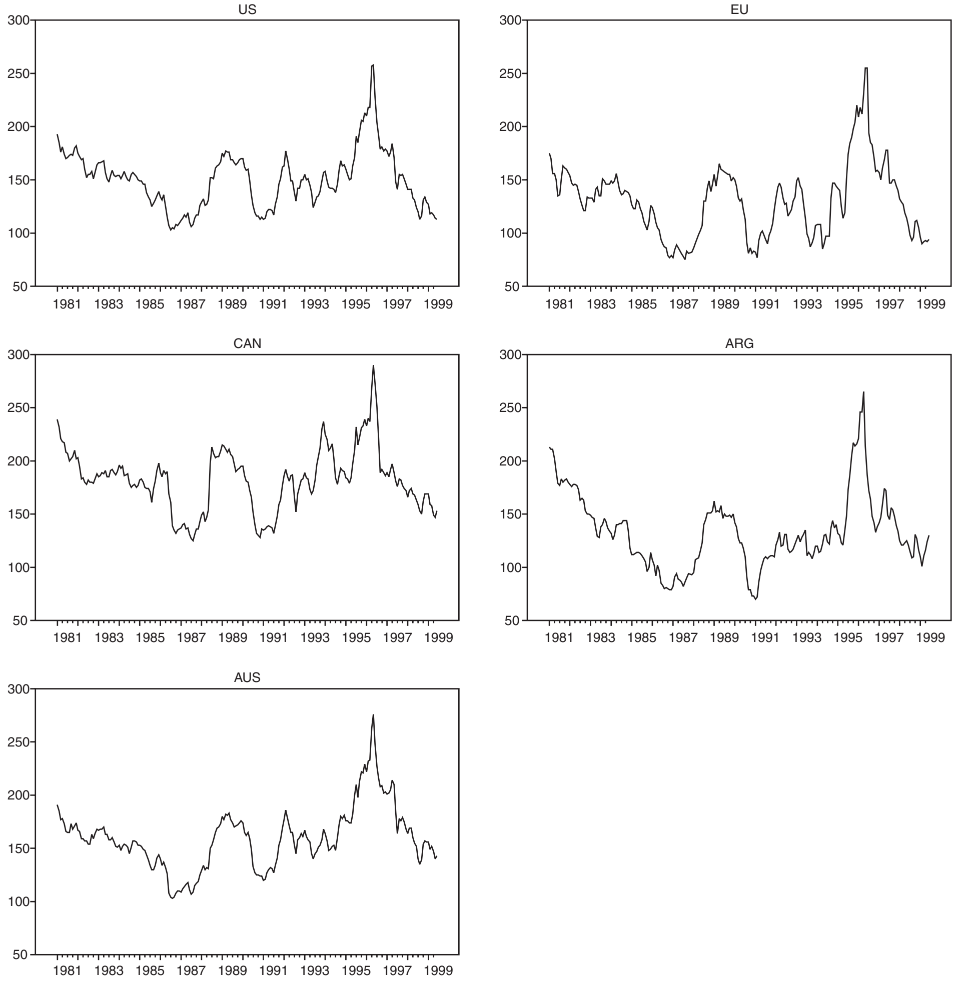


FIGURE 2: Plots of Historical Data on World Wheat Prices, 1981–1999.
In all cases the y-axis is U.S. dollars per ton; the x-axis is time in months and years, 1981–1999. Abbreviations label each subfigure as United States (US), Canada (CAN), Australia (AUS), European Union (EU), and Argentina (ARG).

Prices in the last two years of the 1980s are above their 1987 lows but they return to a neighborhood of the 1987 low in late 1990 or early 1991. Prices from all five regions move thereafter, generally in an upward direction until early 1996, at which time they decline (irregularly) through the remainder of the 1990s. Although the behavior of prices appears to be similar from the plots, there are differences across regions, so we cannot characterize these prices as being in lockstep with each other.

There exists a common criticism over the use of quoted prices to study export price relationships. The critics argue that quoted prices may not accurately reflect true market prices due to the existence of subsidies and other special sales arrangements. However, complete data on actual prices of market transactions are absent. With some caution in interpreting the empirical results, many previous studies (Goodwin and Schroeder, 1991; Mohanty, Peterson, and Kruse, 1995; Mohanty, Meyers, and Smith, 1999) have used quoted prices based on the belief that there may exist certain positive relationships between quoted prices and realized wheat market prices. We follow this precedent here.

It is important to note that the wheat sector and wheat exports from each of the five regions are subject to numerous regulations, policies, and programs during the sample period. The interplay of these regulations and policies, together with economic considerations, affect the international wheat price relationships in a complex way. Below, we discuss briefly some important policy factors in each of the five regions, with highlights of their more recent market-oriented policy changes.

The U.S. farm programs are probably the most important policy factor influencing U.S. wheat production and exports. The U.S. farm program policy dates back to President Franklin D. Roosevelt's New Deal, when protective federal intervention was deemed essential to stabilize farm income. The Agricultural Adjustment Act of 1938 was the first to establish the basic price support and production control system for nonperishable agricultural commodities. A key component of the system—production inflexibility—affected the U.S. crop production in such a way that only acreage planted with specific program crops qualified to receive government deficiency payments. The deficiency or loan rate payments aimed to cover the difference between target prices and (lower) market prices and were potentially a substantial subsidy. Such a system remained essentially unchanged for more than 50 years. For the first time in 1990, the Food, Agriculture, Conservation, and Trade Act made significant progress in eliminating production control by introducing 25 percent production flexibility to farmers' crop production. The effect of the 1990 Act could be quite limited because it was subject to several serious limitations. The most recent 1996 Federal Agricultural Improvement and Reform (FAIR) Act may force U.S. agricultural production to be driven more by market forces. The 1996 FAIR Act virtually brought full flexibility to grain production, and it replaced the target price or the deficiency payments provision with a series of seven-year annual fixed but declining "transition" payments over the period 1996–2002; these payments do not depend on the amount of crop produced or the level of the market price.

Another directly relevant component of the U.S. farm programs during our study period is the Export Enhancement Program (EEP), which was first introduced in 1985 to counter competition from E.U.-subsidized wheat in international markets. However, under the Uruguay Round of GATT (General Agreements on Tariffs and Trade) agreements concluded in 1994, both the U.S. and the E.U. agreed to reduce the use of export subsidies dramatically. Thus, the EEP expenditures were capped in the 1996 FAIR Act and its importance declined after 1996.

Since its creation, the E.U. has aimed to establish an integrated market. In the case of agricultural markets, this effort is assisted by the Common Agricultural Policy (CAP), the backbone of which is a common price policy. Prior to the 1992 CAP reform, the E.U. adopted a package of support and intervention prices along with other policies on an annual basis. This price package played a central role in agricultural policy. E.U. wheat production and exports were strongly influenced by support prices. In the past, the E.U. often relied on export subsidies to dispose of its grain production surpluses. The new limits on subsidies in the Uruguay Round of GATT agreements mean that the E.U. can no longer rely on the world market to absorb all its surpluses. In 1992, the E.U. began its more market-oriented CAP reform. The reform includes substantial reductions in support prices including the use of export subsidies. The reform designed to promote use of grains within the E.U. and curb agricultural surpluses. Rising grain consumption within the E.U. can reduce pressure to aggressively use export subsides as a supply management tool. The CAP reform made the most significant change in the grains sector. The grains support price in 1995–1996 was 33 percent lower than in 1992–93.

The Canadian internal rail-freight subsidy and the Canadian Wheat Board are the two most important factors shaping Canada's wheat export trade. Under the Canadian Western Grain Transportation Act, the Canadian rail-freight subsidy provided transportation subsidies for Canadian grain delivered to western and eastern Canadian ports, which was considered by many U.S. policymakers to be an unfair practice that resulted in increased exports of Canadian grain to the U.S. This subsidy, which had existed for several decades, was eliminated in August 1995. The CWB continues to influence Canadian wheat marketing and exports. The CWB is the single-desk seller (sole seller) of western Canadian wheat and barley for export destinations. The current CWB was created by the Canadian Wheat Board Act in 1935 as a result of Great Depression-generated low wheat prices and large stockpiles of grains. The CWB operates as a marketing agency for producers and has adopted the maximization of returns from sales of wheat and barley as its objective. Single-desk selling is probably the CWB's greatest asset because it arguably may give the CWB a monopoly power to create pricing differentials (often referred to as pricing to market). In fact, a major perceived benefit of the CWB for Canadian wheat producers is the additional producer revenue generated by the ability of the CWB to carry out price discrimination in international markets, which has triggered several recent investigations by the U.S. International Trade Commission in 1990, 1994, and 2001.

Australian wheat marketing and exports are dominated by its wheat board, the AWB. The current AWB was established in 1939 during the Second World War. The AWB and CWB have traditionally been viewed almost as sister agencies. Historically, these two agencies had similar characteristics including the single-desk export monopoly, and price and cost pooling. However, since the early 1990s, the similarities between the CWB and the AWB have diverged and the importance of their differences is becoming increasingly apparent (Carter and Wilson, 1997). AWB reforms are far ahead of those in Canada and the AWB may be more responsive to changing world market conditions, compared to the CWB. Recently, the AWB has been restructured as a holding company to adopt a more commercial approach of its operation. Nevertheless, its single-desk export monopoly power remains intact. More details regarding the operation of the AWB and its emerging differences from the CWB are available in Carter and Wilson (1997).

Finally, the Argentina government does not have a direct role in the marketing of wheat. As a developing country, Argentina historically suffered from instable macroeconomic climates. In the last decade, Argentina's wheat marketing system has undergone fundamental changes through the privatization program and other economic reforms. A particularly important policy factor is the establishment of MERCOSUR (the Southern Cone Common Market), which was created in March 1991 with the signing of the treaty of Asuncion by Argentina, Brazil, Paraguay, and Uruguay. The MERCOSUR members eliminated tariffs among themselves and adopted a common tariff against the rest of the world. Since the creation of MERCOSUR, Argentina wheat exports to other MERCOSUR members have increased dramatically. Arguably, whether and how these policies and policy changes might effectively affect the pattern of wheat price relationships in the international market may require empirical testing.

## 4. EMPIRICAL ANALYSIS

### *Cointegration Analysis and Error Correction Modeling*

The empirical analysis is based on cointegration and the error correction model. The cointegration analysis in this study employs the procedure developed by Johansen and Juselius (1992, 1994) and Johansen (1991, 1992a). All estimation and hypothesis testing is conducted with the CATS in RATS program as described in Hansen and Juselius (1995). Let $\mathbf{X}_t$ denote a vector that includes the market prices $p$ for the five countries under consideration, with $p = 5$ and $\mathbf{X}_t = \begin{bmatrix} X_{1t} \\ X_{2t} \\ X_{3t} \\ X_{4t} \\ X_{5t} \end{bmatrix}$ in this study, where the subscript 1 represents U.S.; 2 represents Canada; 3, Australia; 4, the E.U.; and 5, Argentina and the process can be modeled in an error correction model (ECM)

$$H_0:\ \Delta\mathbf{X}_t = \Pi\mathbf{X}_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta\mathbf{X}_{t-i} + \mu + e_t (t = 1, \dots, T) \tag{1}$$

We first determine the number of cointegrating vectors $r$ as

$$H_1(r)\colon \Pi = \alpha\beta'$$

Given a VAR model with a selected lag length of three (selected using Schwarz criteria on a levels VAR), we investigate the number of long-run "stationary" relationships present in the system of five variables.

In Table 1, we give the trace-test statistics on the rank of $\Pi$, which is equal to the number of cointegrating vectors $r$. The trace tests for both a constant within and outside the cointegrating vector(s) are presented. Determination of the rank of $\Pi$ depends on how $\mu$ enters into the ECM—either as a constant in the cointegrating vector or as a time trend in the original levels representation. To deal with this problem, Johansen (1992a) proposed a sequential testing procedure with respect to the rank of $\Pi$. If there is a linear

TABLE 1: Trace Tests on Order of Cointegration on Wheat Prices

| $H_0$: Rank | Trace* | C(5 percent)* | Decision | Trace | C(5 percent) | Decision |
|---|---|---|---|---|---|---|
| $r = 0$ | 85.92 | 75.74 | Reject | 85.16 | 68.68 | Reject |
| | (84.23) | (75.74) | (Reject) | (83.49) | (68.68) | (Reject) |
| $r \leq 1$ | 51.25 | 53.42 | Fail | 50.64 | 47.12 | Reject |
| | (52.62) | (53.42) | (Fail) | (51.97) | (47.12) | (Reject) |
| $r \leq 2$ | 30.56 | 34.80 | Fail | 30.09 | 29.38 | Reject |
| | (28.74) | (34.80) | (Fail) | (28.10) | (29.38) | (Fail) |
| $r \leq 3$ | 12.69 | 19.99 | Fail | 12.23 | 15.34 | Fail |
| | (12.95) | (19.99) | (Fail) | (12.34) | (15.34) | (Fail) |
| $r \leq 4$ | 1.87 | 9.13 | Fail | 1.74 | 3.84 | Fail |
| | (2.93) | (9.13) | (Fail) | (2.75) | (3.84) | (Fail) |

Trace* and C(5 percent)* refer to the Trace statistic and critical values at the 5 percent significance level with a constant in the cointegrating vector, respectively. Trace and C(5 percent) refer to Trace statistics and critical values at the 5 percent significance level with a constant outside the cointegrating vector, respectively. The Trace test considers the hypothesis that the rank of $\Pi$ is less than or equal to $r$. Entries in the columns labeled "Decision" refer to the decision to "Reject" or "Fail to Reject" the null hypothesis listed in the far left column. Critical values are taken from Hansen and Juselius (Table B.2 for C*; Table B.3 for C). Tests reported not in parentheses are on unlogged data. The entries in parentheses are associated with tests on logged (natural logarithm) data.

trend in the model, we label this hypothesis $H_1(r)$. This hypothesis is an unrestricted case. If there is no linear trend in the model, we label the hypothesis $H_1(r)^*$, which is restricted. The sequential testing procedure suggests testing hypotheses in the following order: $H_1(0)^*$, $H_1(0)$, $H_1(1)^*$, $H_1(1) \ldots H_1(p)^*$, and $H_1(p)$. We stop testing and accept the associated hypothesis at the first failure to reject the null hypothesis in this sequence.

Following the sequential testing procedure of Johansen (1992a), we read Table 1 from left to right and from top to bottom. We first fail to reject the null hypothesis of rank $\Pi$ being less than or equal to unity in the case of a constant in the cointegrating vector [$H_1(1)^*$]. Thus, we have one cointegrating vector with a constant within the cointegrating space among five wheat price series.[3,4]

It is possible that our single cointegrating vector may arise because one of the five series is itself stationary and the other four series are not related in a cointegrating vector; see Hansen and Juselius (1995, p. 11) for further discussion of this possibility. In Table 2 we offer two tests on each series of this possibility. First, we offer Dickey-Fuller tests of the null hypothesis that each series is itself nonstationary. Here we fail to reject the null hypothesis on each market at the 5 percent significance level. As an alternative to these tests on the null of nonstationarity, we test the null hypothesis that each series is stationary. Conditional on one cointegrating vector (found in Table 1) this hypothesis is a test of zero restrictions on four beta coefficients on the cointegrating vector. Under the null hypothesis the test statistic is distributed chi-squared with four degrees of freedom. We reject the null of stationarity at very low $p$-values ($<.00$), for each series.

One hypothesis that is inconsistent with the result here is that for $p$ markets connected by pure competition (a free flow of information and the possibility of arbitrage—in our case it is plausible that wheat could be moved from one market to another by ocean-going ships or by rail between the U.S. and Canada), we should observe $p$-1 (independent) long-run relationships or cointegrating vectors among $p$ market prices (Kuiper, Lutz and Tilburg, 1999). This is a dynamic statement of the static proposition of Samuelson (1952) on

[3]As an alternative to the Trace test on the number of cointegrating vectors, we considered scoring alternative error correction models with Schwarz-loss at $r=1,\ldots, r=5$, both with and without a constant (the latter in parentheses below) in the cointegrating space. Results for unlogged data on the period 1981:2–1999:6 are given as follows: $r=1$: 17.752 (17.848); $r=2$: 17.836 (17.907); $r=3$: 17.905 (17.951); $r=4$: 17.952 (17.976); and $r=5$: 17.986 (17.986). Thus, Schwarz-loss is minimized at $r=1$ for the constant inside the cointegrating space.

[4]Readers may be interested in results for logarithmic-transformed data. We present such result on cointegration rank in parentheses in Table 1. These results are qualitatively the same as those found for unlogged data, so we restrict our analysis in subsequent tables and figures to the unlogged data. In addition, readers may also be interested in whether the number of cointegrating vectors has changed over time due to changing policies of any one of the five governments or trading agencies. Accordingly, we explored time varying patterns of cointegration by recursively calculating the trace test at each data point over the period 1995:1–1999:6. In all cases we have at least one cointegrating vector and almost never more than one. These test results are available from the authors.

TABLE 2: Tests of Hypotheses of Nonstationarity and Stationarity on Wheat Price from the Five Regions

| Market | Dickey-Fuller | Likelihood Ratio Test |
|---|---|---|
| | Null of Nonstationarity | Null of Stationarity ($p$-value) |
| U.S. | −1.98 | 31.12 (.00) |
| Canada | −2.20 | 31.27 (.00) |
| Australia | −1.74 | 31.40 (.00) |
| European Union | −2.01 | 30.85 (.00) |
| Argentina | −2.23 | 30.82 (.00) |

The Dickey-Fuller statistic should be compared to the critical value given of −2.89. Reject the null hypothesis for calculated values less than this critical value. Tests of the hypotheses on the logarithm of price in each country give similar results. For example, the Dickey-Fuller test for log data on the U.S., Canada, Australia, European Union, and Argentina are given as −1.83, −2.10, −1.68, −1.96, and −2.14, respectively. Augmented Dickey Fuller tests with lags of the dependent variable of 1 or 2 give qualitatively similar results in both logged and unlogged data.

The likelihood-ratio statistic is to be compared to the tabular chi-squared distribution with four degrees of freedom (because we put four zero restrictions on the one cointegrating vector found in Table 1). The likelihood ratio tests on the null of stationarity for the logarithm of each series are given (in the same order) as: 30.75, 30.79, 30.79, 30.72, and 30.76. We reject the null hypothesis that the logarithm of wheat price from each region is stationary at very low levels of significance.

price relationships among geographically separated markets. In the case of nonstationary wheat prices and stationary transport prices, this is an immediate implication of the "Law of One Price" (LOP) because efficient trade and arbitrage activities will ensure that prices for a homogeneous commodity in geographically dispersed markets will equalize such that spatial price differentials are always less than or equal to transaction costs (Kuiper, Lutz, and Tilburg, 1999). However, for two reasons we may not expect to observe $p$-1 cointegrating vectors among $p$ market prices in this case. First, as pointed out by Mohanty, Peterson, and Kruse (1995, p. 357), the export market concentration (i.e., only a small number of major exporters), government intervention support, and product differentiation in the international wheat market generally support the contention that the international wheat market may not be perfectly competitive. This deviates from the underlying assumption of the LOP on competition. Second, because we do not measure transportation costs between each market, and others have shown these to be nonstationary—see for example Haigh and Holt (2000) for ocean shipping rates on bulk commodities and Bessler and Fuller (2000) for rail rates for wheat—the LOP is not exactly applied here, which should allow for transportation costs in cointegration analysis.[5] Thus, we should not expect that the

[5]As pointed out by Kuiper, Lutz and Tilburg (1999), though more information on transaction costs (e.g., transportation costs) would facilitate the analysis, unfortunately often the only data available are price series.

specific cointegration pattern of $p$-1 cointegrating vectors among $p$ market prices implied by the LOP would necessarily apply here, even in the case of perfect competition.

However, we wish to suggest that imperfect competition may result in certain cointegration relationships through practices of price leadership and strategic interactions among government agents who set price or price policy in at least some of these markets. As stated above, Canada and Australia export wheat through one central marketing board that may seek to extract higher than competitive prices (see United States International Trade Commission, 2001). Furthermore, historically the E.U. and the U.S. have (over much of our study period) engaged in export restitution (the E.U.) and export enhancement (the U.S.) programs to subsidize the export of wheat to international markets. In discussing a similar set of market institutions in Canadian agriculture, Benson et al. pointed out that "No generalizable theoretical model exists which claims to predict precisely the dynamic adjustment process in an oligopoly/oligopsony market. Every theoretical model implies a set of reaction functions . . . or strategies . . . , but the time path of the reactions and feedbacks depends on the characteristics specific to the industry in question . . ." (1994, p. 679). A priori, our expectation is that the market price in one or more of these markets will not move too far from the market price of the others before a government-induced adjustment is made to restore certain long-run relations between or among the market prices (for at least some of these markets).

Given one cointegration vector, it is of considerable interest to know whether each market enters the vector and whether each market, in turn, responds to perturbations in the vector. Here we investigate these questions. First we conduct a test of exclusion from the cointegration vector. The hypothesis test can be expressed as

$$H_2\colon\ R'\beta = 0$$

The null hypothesis is that each series is not in the long-run equilibrium (the cointegration vector), or stated alternatively, the $i$th column of the $\Pi$ matrix is zero. Table 3 presents results from these tests in the rows labeled $\beta_i = 0$, for $i = 1, 2, 3, 4$, and 5. These tests ask whether region $i$ can be omitted from the cointegrating vector. Under the null hypothesis, region $i$ is not in the vector, and the test statistic is distributed chi-squared with one degree of freedom. We fail to reject the hypothesis for Canada and Australia markets at the 5 percent significance level. However, we can only reject the hypothesis for the Australian market at the 10 percent significance level. Interestingly, prices from the two markets with wheat boards (i.e., Canada and Australia) are excluded from the cointegration vector. This may be the evidence that the monopoly power of marketing from these two markets cause their prices to constantly deviate from the world equilibrium price relationship. The other three markets, the U.S., Argentina, and the E.U. are in the long-run (cointegrating) relation.

TABLE 3: Tests of Hypotheses on the Cointegration Space

| Hypothesis | Degrees of Freedom | $\chi^2$ Test Statistics | Decision |
|---|---|---|---|
| $\beta_1 = 0$ | 1 | 10.38 | Reject |
| $\beta_2 = 0$ | 1 | .08 | Fail |
| $\beta_3 = 0$ | 1 | .21 | Fail |
| $\beta_4 = 0$ | 1 | 5.52 | Reject |
| $\beta_5 = 0$ | 1 | 5.53 | Reject |
| $\alpha_1 = 0$ | 1 | 1.47 | Fail |
| $\alpha_2 = 0$ | 1 | 1.21 | Fail |
| $\alpha_3 = 0$ | 1 | .10 | Fail |
| $\alpha_4 = 0$ | 1 | 6.43 | Reject |
| $\alpha_5 = 0$ | 1 | 2.49 | Fail |
| $\beta_2 = \beta_3 = \alpha_1 = \alpha_2 = \alpha_3 = \alpha_5 = 0$ | 6 | 15.56 | Reject |
| $\beta_2 = \beta_3 = \alpha_1 = \alpha_2 = \alpha_3 = 0$ | 5 | 8.36 | Fail |

Subscripts indicate markets as follows: Market 1 is the United States, Market 2 is Canada, Market 3 is Australia, Market 4 is the European Union, and Market 5 is Argentina. The column labeled “Decision” refers to the decision to reject or fail to reject the hypothesis at a 5 percent significance level.

The weak exogeneity of each price series $X_i$ relative to the long-run equilibrium is also of interest; see, for example, Johansen (1992b, p. 390) for a formal discussion on weak exogeneity. The hypothesis is framed as

$$H_3\colon\ B'\alpha = 0$$

The null hypothesis is that each variable does not respond to perturbations in the long-run relationship, that is, the $i$th row of the $\Pi$ matrix is zero. In other words, we test that the $i$th row of $\alpha$ has its element equal to zero. If any row of $\alpha$ is zero, that variable does not respond to the disequilibrium among the variables and we would not reject the null hypothesis (that $\alpha = 0$). Results of testing $H_3$ for weak exogeneity of series $i$, that is, $\alpha_i = 0$ ($i = 1, 2, 3, 4, 5$), are summarized in Table 3. We find that $\alpha_1$, $\alpha_2$, $\alpha_3$, and $\alpha_5$ are not significantly different from zero at the 5 percent level. We find that $\alpha_4$ is significantly different from zero at the 5 percent level. The test result on $\alpha_5$ is borderline, suggesting that Argentina may, in fact, respond to shocks in the cointegrating vector.

Finally, we tested two joint hypotheses involving both $\beta$ and $\alpha$. Following the results on individual $\beta_i$ and $\alpha_i$, we considered the joint hypothesis $\alpha_i = 0$ ($i = 1, 2, 3$, and 5) and $\beta_2 = \beta_3 = 0$. We reject this hypothesis (see Table 3). We also investigated the hypothesis that $\alpha_1$, $\alpha_2$, and $\alpha_3$ are equal to zero and $\beta_2 = \beta_3 = 0$. We fail to reject this last hypothesis. This last result indicates that Argentina, as well as the E.U., may respond to shocks in the cointegrating vector. In sum, the above finding can be summarized as the following long-run relationship among our five market prices

$$\alpha\beta'\mathbf{X}_{t-1} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ -1.34 \\ 1.23 \end{bmatrix} [-0.213 \quad 0 \quad 0 \quad 0.091 \quad 0.067 \quad 11.881] \begin{bmatrix} X_{1t-1} \\ X_{2t-1} \\ X_{3t-1} \\ X_{4t-1} \\ X_{5t-1} \\ 1 \end{bmatrix}$$

We investigated the forecast performance of an error correction model over the period 1995:1–1999:6. Here we reestimated an error correction model over the period 1981:1–1994:12, with one cointegrating vector and forecasted ahead five periods: 1995:1, 1995:2, 1995:3, 1995:4, and 1995:5. We then observed the actual wheat price in each country for 1995:1, reestimated the error correction model on data 1981:1–1995:1, and forecasted wheat price in each country for the five subsequent periods (1995:2–1995:6). (Actually, the *forecast* and *Theil* commands in RATS (Doan, 1996) does this recursive forecasting and forecast evaluation as standard software commands). Table 4 gives root mean squared forecast errors (MSFE) associated with this forecasting exercise for each region. Forecasts from the error correction model are compared with forecasts from a levels vector autoregression, computed recursively in the same manner as that described for the ECM above.[6] We present three horizons, one-, two-, and five-month ahead forecasts, for each model (ECM and VAR) for each region. The results reported are reflective of results at different horizons (the complete result is available upon request). The ECM results in lower root mean squared errors in 12 of the 15 comparisons. However, the MSFEs for both models are quite close to one another, particularly at short horizons (e.g., one- and two-months ahead), suggesting that there may be no significant difference in forecasting performance between the models at short horizons. We applied the (modified) Diebold-Mariano test of significant differences in mean squared forecast errors at these three horizons (see Harvey, Leybourne, and Newbold, 1997) and found that only at the five-month horizon could we reject the null hypothesis that the mean squared errors generated by the ECM and the levels VAR were equal (at a 5 percent level of significance). Test statistics for the five-month horizon are given in the footnote to Table 4.

Overall, though the ECM summarizes the dynamic interactions that each market price has with other market prices, it is well recognized that like the standard VAR, the individual coefficients of the ECM are difficult to interpret, which may cause difficulty in exploring the short-run dynamic structure.

[6]Several studies (e.g., Bessler and Fuller, 1993; Lin and Tsay, 1996) have shown that an ECM can outperform a first-difference VAR, but not a levels VAR. We also compared the forecasting performance between the ECM and the first-difference VAR and the result (available upon request) is more mixed.

TABLE 4: Root Mean Squared Forecast Error on Out-Of-Sample Forecasts from an Error Correction Model (ECM) Versus a Levels Vector Autoregression (VAR) on Prices from Five Markets, 1995:1–1999:6

| Horizon (steps ahead) | RMSM ECM | RMSM VAR | Observations |
|---|---|---|---|
| | United States | | |
| 1 | 10.96 | 11.13 | 54 |
| 2 | 17.43 | 18.33 | 53 |
| 5 | 29.89 | 35.09 | 50 |
| | Canada | | |
| 1 | 10.60 | 10.79 | 54 |
| 2 | 16.73 | 17.66 | 53 |
| 5 | 30.18 | 36.21 | 50 |
| | Australia | | |
| 1 | 9.82 | 9.80 | 54 |
| 2 | 16.25 | 16.93 | 53 |
| 5 | 26.91 | 32.08 | 50 |
| | European Union | | |
| 1 | 10.29 | 10.19 | 54 |
| 2 | 17.97 | 18.12 | 53 |
| 5 | 34.42 | 38.74 | 50 |
| | Argentina | | |
| 1 | 14.43 | 14.64 | 54 |
| 2 | 23.54 | 24.49 | 53 |
| 5 | 43.14 | 47.62 | 50 |

The differences in mean squared errors (MSE) at the five month horizon are all significantly different from zero at the five percent level. The modified Diebold-Mariano test described in Harvey, Leybourne, and Newbold (1997), results in the following $t$-statistics on the null hypothesis that the mean squared error from the levels VAR is equal to the mean squared error from the ECM (i.e., $MSE_{VAR} - MSE_{ECM} = 0$): 2.29 (U.S.), 2.28 (Canada), 2.80 (Australia), 3.10 (E.U.) and 2.96 (Argentina). Comparing these statistics with student $t$-distribution with $(n-1) = 49$ degrees of freedom results in a rejection of the null in each case. No differences (at usual levels of significance) were found in mean squared errors at horizons 1 and 2. We did not test other horizons.

Our tests of cointegration offered in Table 1 were made over data 1981:1–1999:6. If we re-run these tests over the period 1981:1–1994:12 we find, again, one cointegration vector. Trace-test statistics ($T$) for this subinterval with the constant inside the cointegration vector (with 5 percent critical values in parentheses) are given as: $H_0$: $r = 0$, $T = 87.33$ (75.74); $H_0$: $r \leq 1$, $T = 49.21$ (53.42); $H_0$: $r \leq 2$, $T = 28.67$ (34.80); $H_0$: $r \leq 3$, $T = 15.70$ (19.99); $H_0$: $r \leq 4$, $T = 6.63$ (9.13). Test results for the constant outside the cointegrating vector are not reported, but offer similar results.

Accordingly, innovation accounting may be the best description of the dynamic relationship among multiple time series, whether cointegrated or not (Sims, 1980; Lutkepohl and Reimers, 1992; Swanson and Granger, 1997). The parameters on the above ECM—Equation (1)—can be partitioned to provide useful information for this purpose. The parameters obviously relevant to short-run dynamic structure are those of $\alpha$ and $\Gamma_i$ (Johansen and Juselius, 1994). The imposition of the cointegration constraint is also much needed in a cointegrated VAR analysis because it recently has been demonstrated to be crucial in yielding consistent impulse responses and forecast error decompositions (Phillips, 1998). The information on the long-run cointegration relationship can be identified through testing hypotheses on the $\beta$. Most importantly, the contemporaneous causal structure on innovations can be identified through the directed graphs analysis of the correlation (covariance) matrix of $\hat{e}_t$ (Spirtes, Glymour, and Scheines, 1993; Pearl, 1995, 2000; Swanson and Granger, 1997; Bessler and Yang, 2003), which provides a data-determined solution to the basic problem of orthogonalization of residuals from the ECM, and thus is critical to impulse response analysis or forecast error variance decompositions of a cointegrated VAR. Econometric techniques for cointegration analysis and error correction modeling are well presented elsewhere (Johansen, 1991; Johansen and Juselius, 1992, 1994), so this paper only pays particular attention to recent advances in directed graph theory, as presented previously.

*Directed Graphs and Innovation Accounting Analysis*

The dynamic price relationships are summarized through analysis of both forecast error variance decomposition and impulse response functions in this paper. We manipulate the parameters of the estimated ECM to derive the corresponding levels VAR representation. We then conduct impulse response analysis and forecast error variance decompositions based on this equivalent levels VAR to summarize the dynamic interactions among the five market prices.

The method for treating contemporaneous innovation correlation is crucial to the study of impulse responses or forecast error variance decomposition (Swanson and Granger, 1997). We followed the factorization commonly referred to as the "Bernanke ordering" that requires writing the innovation vector $\mathbf{e}_t$ from the estimated error correction model as: $\mathbf{A}\mathbf{e}_t = \mathbf{v}_t$, where, in our case, $\mathbf{A}$ is a $5 \times 5$ matrix and $\mathbf{v}_t$ is a $5 \times 1$ vector of orthogonal shocks. It was common in earlier VAR-type analyses to rely on a Choleski factorization, so that the $\mathbf{A}$ matrix is lower triangular, to achieve a just-identified system in contemporaneous time. We apply directed graph algorithms as discussed above to place zeros on the $\mathbf{A}$ matrix. A directed graph is an assignment of causal flow (or lack thereof) among a set of variables (vertices) based on observed correlation and partial correlation. Similar to the strong contemporaneous correlations (with most being around 0.5) documented in Goodwin and Schroeder (1991), our five variable error correction model based on the identifying restrictions results in the following innovation correlation matrix (lower triangular entries only are printed in order: $e_1$, $e_2$, $e_3$, $e_4$, and $e_5$.)

$$\mathbf{V} = \begin{bmatrix} 1.0 & & & & \\ 0.56 & 1.0 & & & \\ 0.84 & 0.64 & 1.0 & & \\ 0.58 & 0.37 & 0.55 & 1.0 & \\ 0.30 & 0.27 & 0.35 & 0.41 & 1.0 \end{bmatrix}$$

Directed graph theory explicitly points out that the off-diagonal elements of the scaled inverse of this matrix (**V** or any correlation matrix) are the negatives of the partial correlation coefficients between the corresponding pair of variables, given the remaining variables in the matrix (Whittaker 1990, p. 4). Directed graphs as given in Spirtes, Glymour, and Scheines (1993), provided an algorithm (PC algorithm) for removing edges between markets and directing causal flow of information between markets. As discussed previously, the algorithm starts with a complete undirected graph in which innovations from every variable are connected with innovations from every other variable of the system. The algorithm removes edges sequentially between variables based on the observed zero correlation and partial correlation (conditional correlation). As illustrated below, the notion of sepset is then used to assign the direction of causal flow between variables that remain connected after all possible conditional correlations have been passed as nonzero.

The analysis of directed graphs is actually carried out using the software TETRAD II (Scheines et al., 1994), which applies PC algorithm and its more refined extensions. At the 5 percent significance level, we find the undirected edges as given in Figure 3 after removing the insignificant edges. Note in the figure and the discussion below we use the following symbols: US = United States, CA = Canada, AU = Australia, EU = European Union, and AR = Argentina. Specifically, we remove the edge between Canada and the European Union by conditioning on Australia because the conditional correlation between CA and EU given AU is 0.0325 (represent this conditional

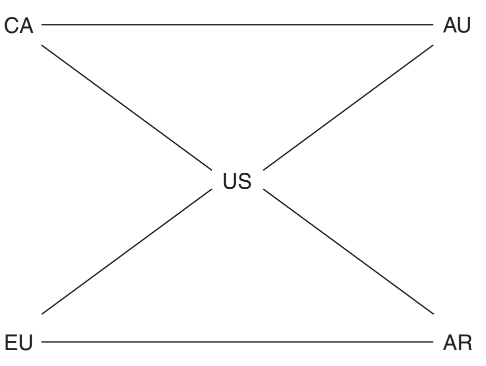


FIGURE 3: Undirected Graph for on Innovation on Wheat Prices from Five Markets.

CA = Prices from Canada; AU = Prices from Australia; US = Prices from the United States; EU = Prices from the European Union; AR = Prices from Argentina.

correlation as ρ(CA, EU|AU)). The associated $p$-value for this correlation is 0.63, rather strongly suggesting that this edge should be removed. The edge between Canada and Argentina is removed again by conditioning on Australia, as ρ(CA, AR|AU) = 0.0358, which has a $p$-value of 0.598. The two other edges removed are those between Australia and Argentina, as ρ(AU, AR|US) = −0.01 ($p$-value of 0.85) and Australia and the European Union, as ρ(AU, EU|US) = 0.09, $p$-value of 0.18. No second- or third-order edge removal is found, as all other conditional correlations at conditional correlation greater than first degree are nonzero (for example, ρ(EU, US|AU, CA) and ρ(CA, US|EU, AR, AU) ≠ 0).

The remaining edges (those given in Figure 3) are directed using sepset, as described above. The end result is given in Figure 4. First, the triple CA—US—EU is directed as CA → US ← EU because the edge between CA and EU is removed by conditioning on AU (so the US is not in the sepset of CA and EU). The intuition behind this pattern of causal flow is worth exploring. There is no edge running between Canada and the European Union. We removed this edge as the conditional correlation between Canada and the European Union given Australia was equal to 0.0325 ($p$-value = 0.63). Thus, the sepset of Canada and the European Union is Australia. We have edges running between Canada and the U.S., and between the European Union and the U.S., so it must be the case that the causal path here is one of an "inverted fork," with Canada and the European Union both causing the U.S. Had the arrows pointed out from the U.S. to both Canada and the European Union (i.e., the U.S. was a common cause), then Canada and the European Union would be correlated unconditionally. In that case, we would have had to rely on a first-order conditional correlation between the Canada and the European Union, conditioning on the U.S. to remove the edge between Canada and the European Union. The same logic would apply if the path was a causal chain Canada → U.S. → European Union. Here again, we would have observed the U.S. in the subset of Canada and the European Union. However,

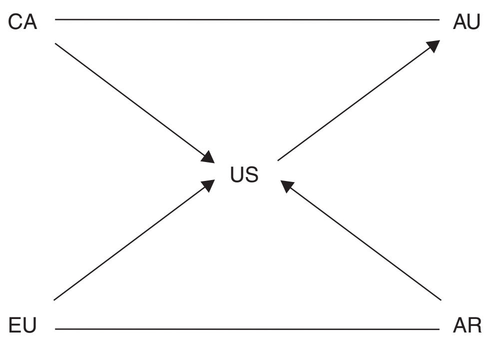


FIGURE 4: Pattern on Innovation on Wheat Prices from Five Markets.
CA = Prices from Canada; AU = Prices from Australia; US = Prices from the United States; EU = Prices from the European Union; AR = Prices from Argentina.

this is not the case because the U.S. is not in the sepset of Canada and the European Union. Thus, the inverted fork should apply.

Similarly, the triple CA—US—AR is directed as CA → US ← AR because the edge between CA and AR is removed by conditioning on AU (rather than US). Finally, the edge between the US and AU is directed by applying the rule given previously—that if $X \rightarrow Y$, $Y$ and $Z$ are adjacent, $X$ and $Z$ are not adjacent, and there is no arrowhead at $Y$, then orient $Y$—$Z$ as $Y \rightarrow Z$. More specifically, here we have a path EU—US—AU. We know that the arrows are not directed inward (both to the US) because the US is in the sepset of EU and AU (we do not have an inverted fork). However, because we know that one arrow runs from EU to the US, then the only possibility is for our path to run from the US to AU, as given in Figure 4.

We label Figure 4 as a "Pattern," because we are not able to direct edge CA—AU and edge EU—AR. That is to say, the correlation and conditional correlation patterns associated with these five markets are not rich enough to assign causal flow between these remaining edges. We need either additional information in terms of substantive subject matter information (knowledge of the intricate working of, say, the Canadian Wheat Board) or inclusion of other markets, which may give us the possibility of more correlation and conditional correlation patterns. This may then help direct the edges between CA and AU and EU and AR. Unfortunately, without this information, any movement toward a directed graph must be viewed with caution. We move in that direction in Figure 5. Here we direct the edge between Canada and Australia as: CA → AU. We offer this edge because the reverse flow of information (CA ← AU) would suggest a cycle between the three markets, CA, US, and

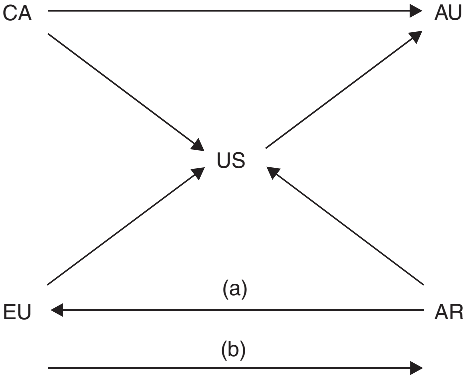


FIGURE 5: Directed Acyclic Graph on Innovations on Wheat Prices from Five Markets.
CA = Prices from Canada; AU = Prices from Australia; US = Prices from the United States; EU = Prices from the European Union; AR = Prices from Argentina.
The arrow labeled (a) indicates causal flow from Argentina to the European Union; whereas the arrow labeled (b) indicates causal flow from the European Union to Argentina.
Both arrows cannot exist at once in a directed acyclic graph.

AU (CA → US → AU → CA). The problem that cyclical graphs present is one of identification. We know of no unique way to define causality from correlations and partial correlations when such cycles characterize information flows. Richardson and Spirtes note that "in contrast to the acyclic graph case almost nothing general is known about how directed cyclic graphs (DCGs) represent conditional independence constraints, or about their equivalence or identifiably properties or about characterizing classes of DCGs from conditional independence relations or other statistical constraints" (1999, p. 254). Hence, though we cannot say that such cycles do not characterize world wheat pricing with a probability of unity, they suggest a pattern for which the graphical literature has not yet reached a consensus.

The other undirected edge present in Figure 4 is that between the European Union and Argentina. Here we consider edges flowing both ways: the European Union causes Argentina and Argentina causes the European Union. That is, in our innovation accounting analysis we present results for both the E.U. causes Argentina and Argentina causes the E.U.

Table 5 contains the forecast error variance decompositions at horizons 0, 1, 12, and 24 months under both the orderings—(a) and (b)—of innovations in contemporaneous time, as generated by the directed graph in Figure 4. We list results for the case of "E.U. causes Argentina" in the row labeled (a) and the results for "Argentina causes the E.U." in the row labeled (b). These values indicate how forecast error variance in each equation is decomposed. The decompositions are helpful in visualizing the relationships among variables in the system. Except for its own innovations (43 to 46 percent), U.S. price variation is explained by innovations in price from Canada (28 to 36 percent) and somewhat by innovations from the E.U. (8 to 13 percent) and Argentina (17 to 25 percent). The relative impact of the E.U. and Argentina on the U.S. price depends on how we model the causal flow in contemporaneous time between these two countries, row (a) or row (b). Together, they explain from 15 percent to just over 25 percent of the variation in the U.S. price at each horizon.

By contrast, Canadian price variation is determined almost solely by its own innovations at all steps (91 to 100 percent). For Canada, it makes little difference how the causal flow between the European Union and Argentina is modeled. The U.S. and Argentina each account for just under 5 percent of the variation in the Canadian price at horizons of 12 and 24 months.

For the Australia series, price variation is most prominently explained by Canada (31 to 43 percent), the U.S. (24 to 41 percent), and Argentina (3 to 25 percent). Canada shows a stronger influence in the short run (0 and 1 months ahead), whereas the U.S. is most prominent in the long run. Interestingly, Argentina explains about 15 to 25 percent of the variation in the Australian price at the 12- and 24-month horizons. There is some modest difference in the role of Argentina, depending on how we model the E.U.-Argentina causal pattern. Australia accounts for less than 5 percent of its own forecast error uncertainty at horizons of 12- and 24-months.

TABLE 5: Variance Decomposition of Wheat Price from Five Markets Based on Bernanke Decompositions

| | Step | U.S. | Canada | Australia | E.U. | Argentina |
|---|---|---|---|---|---|---|
| | | | | US | | |
| (a) | 0 | 46.28 | 36.04 | 0.00 | 12.91 | 4.77 |
| (b) | 0 | 46.28 | 36.04 | 0.00 | 5.61 | 12.06 |
| (a) | 1 | 45.98 | 32.87 | .02 | 10.58 | 10.55 |
| (b) | 1 | 45.98 | 32.87 | .02 | 3.03 | 18.11 |
| (a) | 12 | 43.67 | 27.69 | .37 | 9.68 | 18.59 |
| (b) | 12 | 43.67 | 27.69 | .37 | 1.21 | 27.06 |
| (a) | 24 | 45.46 | 28.41 | .36 | 8.52 | 17.25 |
| (b) | 24 | 45.46 | 28.41 | .36 | .95 | 24.82 |
| | | | | CAN | | |
| (a) | 0 | 0.00 | 100.00 | 0.00 | 0.00 | 0.00 |
| (b) | 0 | 0.00 | 100.00 | 0.00 | 0.00 | 0.00 |
| (a) | 1 | 0.65 | 99.07 | .02 | .05 | .20 |
| (b) | 1 | 0.65 | 99.07 | .02 | .15 | .10 |
| (a) | 12 | 3.82 | 91.54 | .12 | .40 | 4.12 |
| (b) | 12 | 3.82 | 91.54 | .12 | .10 | 4.42 |
| (a) | 24 | 4.43 | 91.03 | .12 | .34 | 4.08 |
| (b) | 24 | 4.43 | 91.03 | .12 | .11 | 4.31 |
| | | | | AUS | | |
| (a) | 0 | 24.35 | 43.29 | 23.05 | 6.79 | 2.51 |
| (b) | 0 | 24.35 | 43.29 | 23.05 | 2.95 | 6.35 |
| (a) | 1 | 32.56 | 37.91 | 13.75 | 5.77 | 10.00 |
| (b) | 1 | 32.56 | 37.91 | 13.75 | 1.24 | 14.53 |
| (a) | 12 | 39.27 | 30.78 | 4.80 | 6.79 | 18.36 |
| (b) | 12 | 39.27 | 30.78 | 4.80 | .44 | 24.71 |
| (a) | 24 | 40.75 | 31.10 | 4.27 | 6.23 | 17.65 |
| (b) | 24 | 40.75 | 31.10 | 4.27 | .33 | 23.55 |
| | | | | EU | | |
| (a) | 0 | 0.00 | 0.00 | 0.00 | 100.00 | 0.00 |
| (b) | 0 | 0.00 | 0.00 | 0.00 | 82.94 | 17.06 |
| (a) | 1 | 8.86 | 5.35 | .33 | 82.70 | 2.75 |
| (b) | 1 | 8.86 | 5.35 | .33 | 60.80 | 24.65 |
| (a) | 12 | 38.34 | 20.98 | .18 | 31.77 | 8.73 |
| (b) | 12 | 38.34 | 20.98 | .18 | 16.32 | 24.18 |
| (a) | 24 | 45.61 | 24.07 | .12 | 24.22 | 5.97 |
| (b) | 24 | 45.61 | 24.07 | .12 | 12.59 | 17.60 |
| | | | | AR | | |
| (a) | 0 | 0.00 | 0.00 | 0.00 | 17.05 | 82.94 |
| (b) | 0 | 0.00 | 0.00 | 0.00 | 0.00 | 100.00 |
| (a) | 1 | .22 | .22 | .21 | 15.24 | 84.11 |
| (b) | 1 | .22 | .22 | .21 | .10 | 99.25 |
| (a) | 12 | 15.89 | 15.52 | 1.23 | 5.96 | 61.39 |
| (b) | 12 | 15.89 | 15.52 | 1.23 | 2.11 | 65.24 |
| (a) | 12 | 23.73 | 20.44 | 1.10 | 3.20 | 51.32 |
| (b) | 24 | 23.73 | 20.44 | 1.10 | 3.02 | 51.70 |

Model (a) refers to the Bernanke decomposition of contemporaneous covariance from a directed graph on innovations given in Figure 4 with the directed edge: EU → AR. Model (b) refers to the directed graph on innovations given in Figure 4 with the directed edge: AR → EU.

In the short run, the E.U. price is most prominently explained by itself. We see clearly how the ambiguity in modeling the contemporaneous causal flow between Argentina and the European Union affects the variance decompositions in terms of the differences in the (a) and (b) rows of the E.U. panel. This ambiguity has no effect on the relative importance of the other participants on the E.U. price (U.S., Australia, and Canada). The ambiguity shows us an approximate 10 to 20 percent difference in allocation of influence between the E.U. and Argentina on the E.U. price at all horizons.

Finally, the Argentina price variation is mostly determined by its own innovations. This is particularly true in the horizons of 0 and 1 month (80 to 100 percent). At the horizons of 12 and 24 months, the price variation is also significantly influenced by the U.S. (15 to 24 percent) and Canada (15 to 20 percent) prices. The influence of the E.U. on Argentina falls to less than 5 percent under either causal ordering at the 24-month horizon.

The use of directed graphs to provide evidence of causality in contemporaneous time is not common in econometric applications, so it is worth contrasting the associated partitions with the more commonly used Choleski factorization of the error covariance matrix. In Table 6 we present error decompositions under two Choleski factorizations. First, rows (a), we order innovations as: US, CAN, AUS, EU, and AR. Second, we order as rows (b): CAN, US, AUS, EU, and AR. Results from Table 4 show a much larger proportion of both U.S. and Canadian price variation attributed to the U.S. when the U.S. is ordered first (a), relative to those proportions found in Table 3. The results in Table 6, associated with Canada ordered first, look similar to the results presented in Table 5 (for both Canada and the U.S.). The Choleski ordering, which places the U.S. first, seems to very much overstate the importance of the U.S. in setting the price in both the U.S. and Canada. An additional difference between the partitions shown in Tables 5 and 6 is observed in the relative importance attributed to Argentina. Its role in price discovery in the U.S., Australia, and Argentina is very much understated in both orderings shown in Table 6. Of course, moving Argentina up from last to third or fourth, above both the European Union and Australia, would reduce the discrepancy between Tables 5 and 6, although it is difficult to say how the research worker would know to do this a priori.

In sum, similar to Goodwin and Schroeder (1991), we find that the U.S. and Canada have strong effects on international wheat market prices. Canada appears to be the most ‘exogenous’ market because it accounts for over 90 percent of its own price variation at all horizons considered. Furthermore, we also find that Argentina has a nontrivial influence on wheat prices in the U.S., Australia, the E.U., and Argentina, especially at the 24-month horizon. Argentina is the next most ‘autonomous’ market, accounting for over 50 percent of its own price variation at all horizons (under either of causal flow patterns between the E.U. and Argentina in contemporaneous time). These results are not found in the studies cited above.

TABLE 6: Variance Decomposition of Wheat Price from Five Markets Based on Choleski Decompositions of Contemporaneous Innovation Covariance

| | Step | U.S. | Canada | Australia | E.U. | Argentina |
|---|---|---|---|---|---|---|
| | | | | US | | |
| (a) | 0 | 100.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| (b) | 0 | 50.86 | 49.14 | 0.00 | 0.00 | 0.00 |
| (a) | 1 | 98.52 | .04 | .04 | .29 | 1.10 |
| (b) | 1 | 51.69 | 46.87 | .04 | .29 | 1.10 |
| (a) | 12 | 95.31 | .15 | .47 | .52 | 3.55 |
| (b) | 12 | 52.13 | 43.33 | .47 | .52 | 3.55 |
| (a) | 24 | 95.65 | .16 | .48 | .78 | 2.92 |
| (b) | 24 | 52.54 | 43.27 | .48 | .78 | 2.92 |
| | | | | CAN | | |
| (a) | 0 | 49.14 | 50.86 | 0.00 | 0.00 | 0.00 |
| (b) | 0 | 0.00 | 100.00 | 0.00 | 0.00 | 0.00 |
| (a) | 1 | 54.71 | 44.87 | .04 | .35 | .03 |
| (b) | 1 | .52 | 99.06 | .04 | .35 | .03 |
| (a) | 12 | 69.04 | 28.88 | .18 | .36 | 1.54 |
| (b) | 12 | 5.16 | 92.76 | .18 | .36 | 1.54 |
| (a) | 24 | 70.60 | 27.32 | .19 | .48 | 1.41 |
| (b) | 24 | 5.65 | 92.27 | .19 | .48 | 1.41 |
| | | | | AUS | | |
| (a) | 0 | 77.97 | 2.17 | 19.86 | 0.00 | 0.00 |
| (b) | 0 | 27.72 | 52.42 | 19.86 | 0.00 | 0.00 |
| (a) | 1 | 85.68 | .87 | 11.19 | .71 | 1.54 |
| (b) | 1 | 37.12 | 49.43 | 11.19 | .71 | 1.54 |
| (a) | 12 | 91.69 | .11 | 3.47 | .94 | 3.80 |
| (b) | 12 | 46.49 | 45.31 | 3.47 | .94 | 3.80 |
| (a) | 24 | 92.38 | .06 | 3.01 | 1.16 | 3.40 |
| (b) | 24 | 47.19 | 45.24 | 3.01 | 1.16 | 3.40 |
| | | | | EU | | |
| (a) | 0 | 26.01 | .12 | .88 | 73.00 | 0.00 |
| (b) | 0 | 15.04 | 11.09 | .88 | 73.00 | 0.00 |
| (a) | 1 | 57.44 | .18 | 1.22 | 40.78 | .38 |
| (b) | 1 | 32.53 | 25.09 | 1.22 | 40.78 | .38 |
| (a) | 12 | 92.63 | .41 | .16 | 5.30 | 1.50 |
| (b) | 12 | 53.42 | 39.62 | .16 | 5.30 | 1.50 |
| (a) | 24 | 95.80 | .52 | .09 | 2.71 | .87 |
| (b) | 24 | 55.99 | 40.34 | .09 | 2.71 | .87 |
| | | | | AR | | |
| (a) | 0 | 25.30 | .03 | 0.00 | 3.35 | 71.31 |
| (b) | 0 | 13.77 | 11.56 | 0.00 | 3.35 | 71.31 |
| (a) | 1 | 28.75 | .02 | .29 | 2.21 | 68.73 |
| (b) | 1 | 15.32 | 13.45 | .29 | 2.21 | 68.73 |
| (a) | 12 | 59.79 | .15 | 1.73 | 3.17 | 35.16 |
| (b) | 12 | 28.06 | 31.88 | 1.73 | 3.17 | 35.16 |
| (a) | 12 | 67.65 | .09 | 1.72 | 4.98 | 25.57 |
| (b) | 24 | 32.75 | 34.99 | 1.72 | 4.98 | 25.57 |

Model (a) refers to the Choleski decomposition of contemporaneous covariance on innovations with the following ordering: US, CAN, AUS, EU, and AR. Model (b) refers to the Choleski decomposition of contemporaneous covariance on innovations with the following order: CAN, US, AUS, EU, and AR.

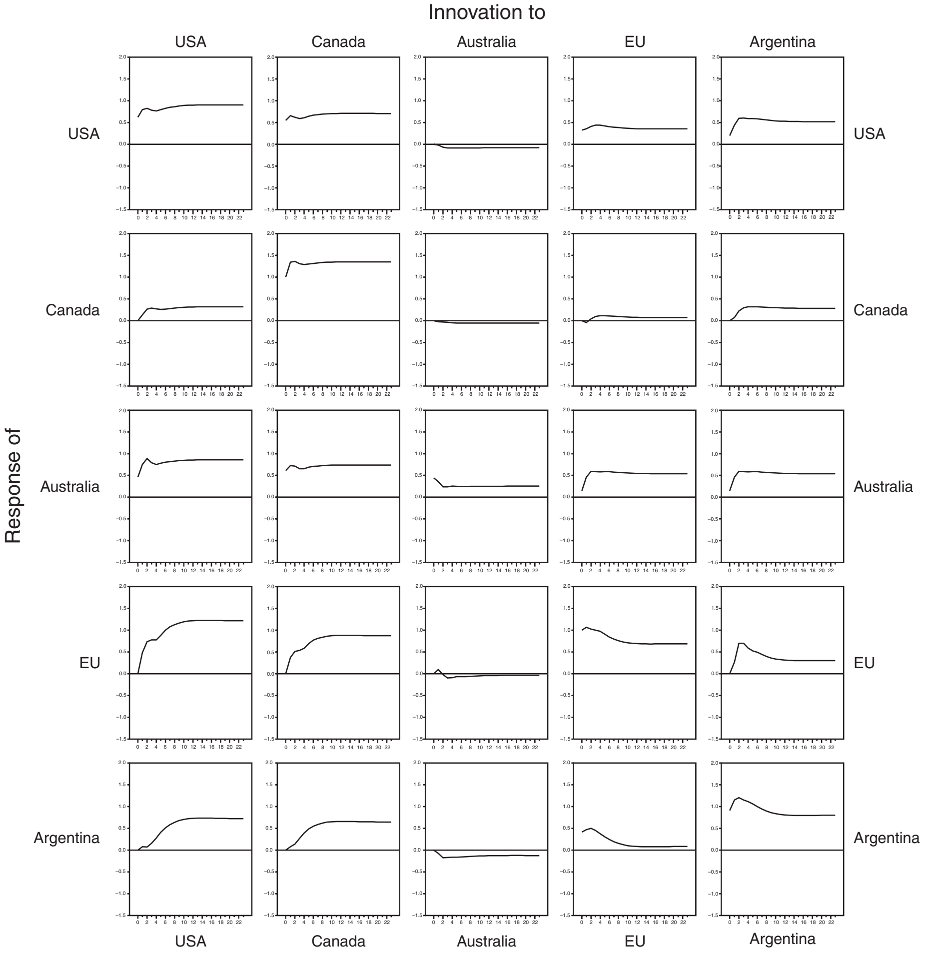


FIGURE 6: Impulse Response of Each Wheat Market Price to a One-Time-Only Shock in Innovations in Each Market Price, European Union Causes Argentina in Contemporaneous Time.

Figures 6 and 7 give impulse responses associated with the error correction model under the ordering of innovations as generated by the directed graph given in Figure 4.[7] Figure 5 shows results in the case that E.U. causes Argentina in contemporaneous time. Figure 6 shows results in the case that

[7]We did not calculate confidence intervals on the impulse response functions. Though such a practice is not a difficult task for a standard VAR with Choleski decomposition, calculating standard errors of impulse response functions and forecast error variance decomposition for an ECM with structural decomposition is much more challenging. We leave such a potentially important offering to the future research.

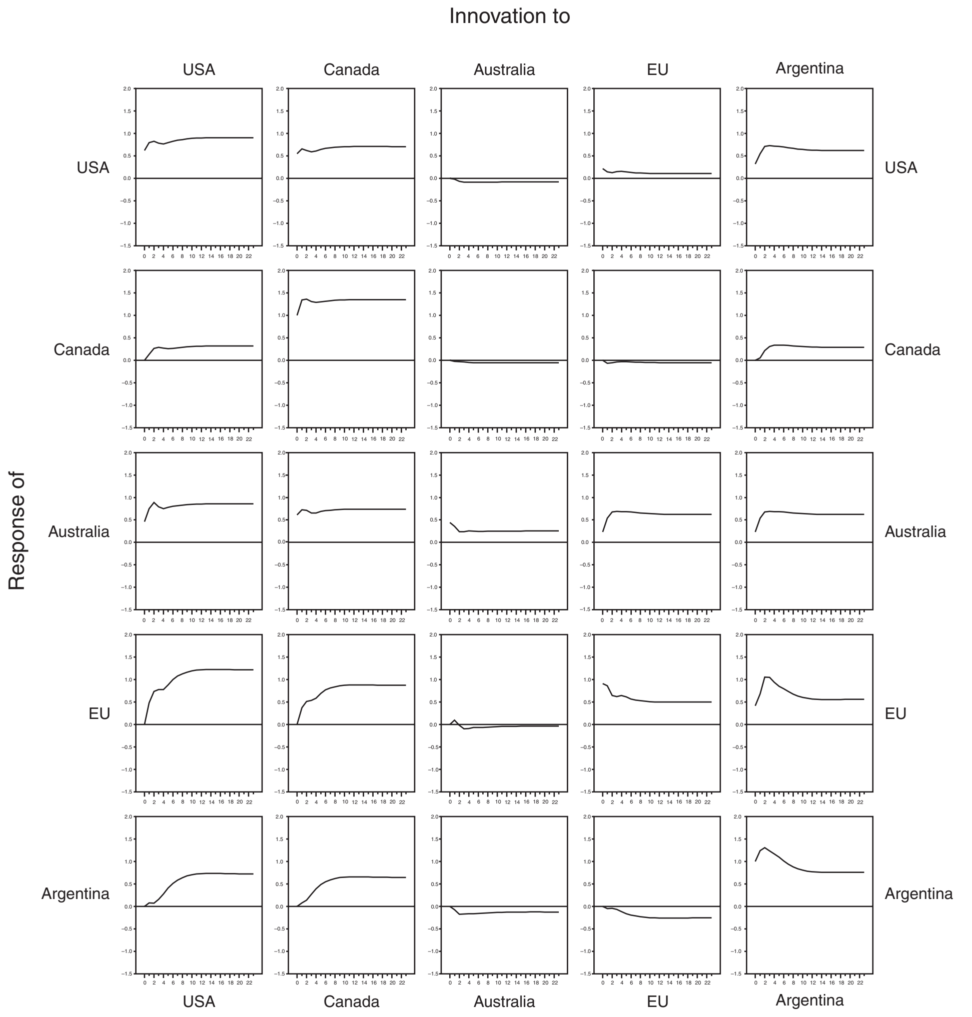


FIGURE 7: Impulse Response of Each Wheat Market Price to a One-Time-Only Shock in Innovations in Each Market Price, Argentina Causes the European Union in Contemporaneous Time.

Argentina causes the E.U. in contemporaneous time. Responses are normalized by the historical innovation standard deviation from each market. Thus, it is possible to make comparisons across different cells of each figure. The results are consistent with results found in the forecast error variance decompositions. All region prices respond positively to a one-time-only shock in the U.S., the Canadian, and the Argentinean price. Australia has little influence on other regions' prices. The European Union's price seems to influence the Australian price in both Figure 6 and 7.

## 5. CONCLUSIONS

This paper reexamines dynamic price relationships in the international wheat market for the years 1981–1999. We study observational data in an error correction framework using directed acyclic graphs (Sprites, Glymour, and Scheines, 1993; Pearl, 1995; Swanson and Granger, 1997; Bessler and Yang, 2003). Prices from the two countries having single state trading boards, Canada and Australia, are found not to be part of the long-run cointegration relation, whereas prices from the European Union, Argentina, and the U.S. are part of the long-run relation. This could be evidence that the monopoly power of marketing from these two markets cause their prices to constantly deviate from the world equilibrium price relationship. Furthermore, prices from the European Union and Argentina are found to respond to perturbations (shocks) in this long-run relation, whereas prices from the other three countries do not respond to such shocks.

In addition, we find strong, contemporaneous correlations among the innovations (residuals) from our error correction process. Such correlations have been documented by others in the literature using similar methods (Goodwin and Schroeder, 1991, p. 242); however, they have yet to be studied with graphical techniques. This study is able to provide evidence previously unavailable on contemporaneous causal relationships among multiple commodity markets for wheat. Nevertheless, some ambiguity remains: in two cases the direction of contemporaneous causal flows was not clear—do price innovations in Argentina cause price innovations in the European Union in contemporaneous time, or is it the reverse? Do price innovations in Australia cause price innovations in Canada in contemporaneous time, or does the reverse direction characterize the information flow pattern between these two markets? We answer the former question by presenting results under both directions of causal flow. Here we find that although differences in dynamic responses are not trivial, the general results do not change: Canada, the U.S., and Argentina are primary points of price discovery. Furthermore, Canada is the most highly exogenous market under both orderings. We rely on a technical consideration—no cyclic graphs—to answer the second question. Of course, this answer should be viewed with caution because cycles may characterize information flows in the world wheat market. However, our ability to unambiguously uncover these cyclic flows with current methods is weak and thus not used here; see Richardson and Spirtes (1999) for a recent attempt at such modeling.

Our proposal to use directed acyclic graphs to help sort out causal flows in contemporaneous time is important because such analysis offers a data-determined (as opposed to a subjectively-determined) pattern for the structural decomposition of VAR residuals. With the above methodological improvements and the assumption of no cyclic graphs, we are able to show that Canada dominates price discovery in the short run of zero-to-one month ahead. Relative to that of Canada, the U.S. has a less dominate role in the short run. Canada substantially affects the prices in all other markets including the U.S. In contrast, the U.S. has a significant impact on the prices in Australia, the E.U., and Argentina, but not on prices from Canada. At horizons of one-to-two years ahead, the U.S. is the dominant market in all countries except Canada. This finding is somewhat different from previous studies, including Goodwin and Schroeder (1991), Mohanty, Peterson, and Kruse (1995), Mohanty, Peterson, and Smith (1996), and Mohanty, Meyers, and Smith (1999).

The findings of this study carry some important implications. First, the results provide evidence that Canada is able to influence price in the international wheat market, particularly in the short run. Similar to Mohanty, Peterson, and Smith (1996), our findings suggest that the U.S. wheat market price is not insulated from Canadian influences. This could be interpreted to support the contention of U.S. wheat producers that Canadian production and export subsidies have undermined the U.S. wheat price support program. However, the caveat is that without further investigation, one cannot say for sure that wheat imports from Canada are directly responsible for price changes in the U.S. because no account has been taken of the high quality and standardization of Canadian Wheat. The causal influence found here may be the result of stringent grading and classification requirements in Canada that allow Canada to exercise price leadership based on product differentiation (Mohanty, Peterson, and Smith, 1996, p. 275). Second, although the CWB may effectively exert market power, the concern that the AWB may practice price discrimination is not supported here. According to Carter and Wilson (1997), the inability of the AWB to price discriminate may be due to either the smaller Australian market share (about 8 percent) in world wheat trade relative to the Canadian market share (about 22 percent), or to the emerging difference between the AWB and the CWB since the early 1990s. The evidence is generally consistent with the argument that the AWB is more responsive to changing world market conditions than the CWB (Carter and Wilson, 1997). Finally, interdependence in the international wheat market implies that independent wheat policy may be undermined. For example, the evidence here that Canada substantially influences the U.S. price and the U.S. substantially influences the E.U. price suggests that the government intervention by the U.S. and the E.U. in the wheat exports were either infeasible or very costly, as was the case during the sample period.

With respect to future research, it has been argued (Protopapadakis and Stoll, 1983) that international commodity price relationships can be investigated in "its purest form" when futures prices are used. Yang, Bessler, and Leatham (2001) further pointed out that an important difference exists between commodity cash and futures markets in the ability of incorporating relevant price information, and that such a difference between commodity cash and futures prices may be more significant for the commodities such as wheat traded largely in the international markets. Hence, additional work to test international wheat price relationships using commodity future prices in different countries and regions (if available) is certainly of interest. Using more recent data since the late 1990s may also help explore a possible structural break due to recently more market-oriented government agricultural policies in major wheat production countries and a freer environment of international trade. Finally, basic research on identifying cyclic graphs with observational data is an area of high research priority.

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