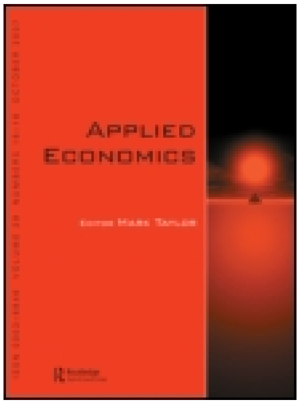

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Dynamic and contemporaneous causality in a supply chain: an application of the US beef industry

Moonsoo Park [a], Yanhong Jin [b] & Alan H. Love [c d e]

[a] Korea institute for Industrial Economics and Trade (KIET), Seoul, the Republic of Korea

[b] Department of Agricultural, Food and Resource Economics, Rutgers University, New Brunswick, USA

[c] Department of Agricultural Economics, Texas A&M University, College Station, USA

[d] Department of Information and Operations Management, Texas A&M University, College Station, USA

[e] Department of Economics and Resource Management, Norwegian University of Life Sciences (UMB), Aas, Norway

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Dynamic and contemporaneous causality in a supply chain: an application of the US beef industry

Monsoo Park[a,†], Yanhong Jin[b,*] and Alan H. Love[c,d,e]

[a] *Korea institute for Industrial Economics and Trade (KIET), Seoul, the Republic of Korea*
[b] *Department of Agricultural, Food and Resource Economics, Rutgers University, New Brunswick, USA*
[c] *Department of Agricultural Economics, Texas A&M University, College Station, USA*
[d] *Department of Information and Operations Management, Texas A&M University, College Station, USA*
[e] *Department of Economics and Resource Management, Norwegian University of Life Sciences (UMB), Aas, Norway*

Causal relationships are used to investigate information flows and directions of control in a decentralized multi-echelon supply chain where no central authority has system level control over optimizing decisions. We use secondary time-series data representing the US beef industry to investigate dynamic and contemporaneous causality based on out-of-sample Granger causality and Direct Acyclic Graphs (DAGs). Results indicate: (i) the US beef supply chain experienced a significant structural change in late 1996 and early 1997 that may be attributed to a weather induced production shock and an apparent turnaround of the cattle cycle; (ii) contemporaneous causalities appear to be stronger and dynamic causalities appear to be weaker after the structural change, suggesting faster and more effective information transmission along the supply chain after the structural change; (iii) contemporaneous information appears to flow from upstream to downstream tiers in the supply chain before the structural break, which reverses after the structural break, suggesting a shift in control from upstream to downstream firms; and (iv) co-use of spot market and contracts to procure strategic inputs by processors appears to allow processors some control of spot price through contract purchases in the post-break period. Our approach could be readily used to investigate other multi-echelon systems.

*Corresponding author. E-mail: yjin@aesop.rutgers.edu
[†] Moonsoo was a doctoral student while working on this article.

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I. Introduction

A decentralized multi-echelon supply chain is a complex and dynamic system that involves multiple economic entities encompassing product production, wholesaling and retailing, where no single entity enjoys control of decision making throughout the value chain (Zhang, 2006; Hwarng and Xie, 2008). Along a decentralized supply chain, material and financial information flows connect participants including: producers, distributors, retailers and customers in both directions (Fiala, 2005: Ferguson and Ketzenberg, 2006). In this environment, the goal is to provide value to consumers through supplying desirable products when and where they are demanded and for each supply chain participant to make a reasonable return from their contribution.

Much literature has focused on the benefits of information sharing to better match supply with demand (see, e.g. Cachon and Fisher, 2000; Sahin and Robinson, 2002, 2005). With full information exchange and properly aligned incentives, the supply chain can efficiently supply products to consumers. However, significant efficiency losses occur when information exchange is hampered or misaligned and conflicting incentives are present. Inefficiencies arise when members in a decentralized supply chain do not have sufficient information or control to implement system wide optimal policies (Zhang, 2006). For example, double marginalization may result when multiple self-interested participants, large enough to influence terms of trade, independently choose prices and production to maximize their individual profit at successive stages in the supply chain (Chopra and Meindl, 2001; Mendelson and Tunca, 2007). With double marginalization, the system as a whole suffers economic losses since retail price is too high and production is too low when compared to an optimized supply chain controlled by a single central decision maker (Cachon, 2003). In other situations, poor coordination can result in lost sales through stock-outs and increased spoilage when excessive inventories result in products that cannot be sold; a particularly costly problem when the product is highly perishable. This situation can become extreme when poor coordination results in delays, oscillations and amplification of changes in order levels creating a bull whip effect in the supply chain (Sahin and Robinson, 2002).

Typical studies of information sharing focus on the effects of information exchange on improving supply chain performance. Information exchange in the supply chain may include: demand at all levels in the channel usually originating with point of sale scanner data, production status and costs, transportation availability and costs, inventory levels and costs, and promotional activities. Most previous research focused on supply chain information sharing and physical flow coordination involves investigations of the effects that changes in decision making control and changes in the timing and specific data and information shared have on system performance. Such studies require considerable information and understanding of specific practices in the value chain. Due to the difficulty in obtaining such information, relatively few empirical studies have been undertaken (Sahin and Robinson, 2002).

We take a different tack. We use secondary time-series data for prices and quantities exchanged, and other pertinent variables at each level in a decentralized multi-echelon supply chain to investigate causalities among these variables. Using out-of-sample Granger causality tests and Direct Acyclic Graphs (DAGs) to examine dynamic and contemporaneous causal linkages between participants we are able to analyse fundamental information flows and control of decision making along a supply chain and how they change through time. Comparison of results between these two causalities has important implications for a value chain. Weak (strong) dynamic causality but strong (weak) contemporaneous causality suggests fast and effective (slow and ineffective) information transmission along a value chain. Effective information transition implies well coordinated transactions so that stock-outs, over-stocks and bullwhip effects should be minimal. In contrast, ineffective information transmission implies lack of coordination so that stock-outs, over-stocks and bullwhip effects may be problematic. Dynamic causality from downstream to upstream along a value chain suggests a possibility of control and first mover advantage by the downstream sector, while causality from upstream to downstream suggests the opposite. In either case, double marginalization is likely. In contrast, strong contemporaneous causality and no dynamic causality imply centralized or coordinated decision making across the entire supply chain. Methodologies employed in this article can be easily applied to other areas besides value chains to uncover causalities in two dimensions. For example, Awokuse (2006) has used similar tests to investigate both dynamic and contemporaneous causalities between exports and productivity growth in Japan.

The US beef supply chain is used as an application. It has experienced a rapid transformation and is becoming more concentrated at both the processor and retail levels. In 2006, the four-firm concentration ratio in the meatpacking industry, measured by the percentage of cattle slaughtered by the four largest firms, was approximately 69% and the

Herfindall–Hirschman Index (HHI), defined as the sum of each firm's squared percentage of market share, was 1382 (Grain Inspection and Packers Stockyard Administration (GIPSA), 2008, table 29 on p. 58).[1] This represents a high degree of market concentration and suggests that packers may be able to exercise considerable control over the supply chain. Indeed, in the last decade, the beef packing industry has made a significant shift from spot market procurement of fed cattle to increased use of forward contracts, packer ownership and marketing/purchasing agreements to procure fed cattle. Collectively, these latter procurement methods have come to be known in the industry as captive supplies.[2] Captive supplies of the top four steer and heifer packers increased from 20.1% of the total steer and heifer procurement in 1997 to 40.4% in 2006 (GIPSA, 2008, table 6 on p. 33). It should also be noted that during this period, supermarket chains had also consolidated operations. Between 1994 and 2004, the top four grocery firms increased their market share from slightly less than 20% to almost 40% (Agricultural Marketing Service (AMS), 2008, figure 14 on p. 24).

Whether higher concentration and more tightly controlled coordination through contract procurement have improved vertical coordination among the various tiers in the supply chain is an important but difficult issue to analyse. However, it is certainly the case that understanding causal linkages along the supply chain has important implications for policy makers, for economic agents within supply chain, and for consumers. Our example is representative of various industries associated with other agricultural products, forest products, natural gas and oil. In each case, exchange at various stages takes place through a combination of spot market and bilateral contracts between participants at successive stages. In these situations, no central authority in the supply chain has system level control over optimizing decisions. Further, little empirical work has been undertaken to investigate information sharing and flow among different parties or how exchange of products is controlled or coordinated among participants. This article sheds light on these issues.

This article is organized into four additional sections. The next section describes empirical methodologies to identify temporal and contemporaneous causalities and to investigate how causality may change when there is a structural break. Section III provides an overview of the US beef supply chain and data descriptions, followed by empirical results in Section IV. Conclusions and policy implications are discussed in the final section.

II. Methodologies

Granger causality is perhaps the most widely used approach to identify dynamic (in temporal sense) causality in economics (Granger, 1969, 1980; Engle and Granger, 1987). It has been implemented in numerous studies, with recent examples including Masih and Masih (1996, 1998) and Kasman and Ayhan (2008). Granger (1969) defines that x_t Granger-causes y_{t+1} if and only if

$$P(y_{t+1} \in A|\Theta_t, x_t) \neq P(y_{t+1} \in A|\Theta_t)$$

for some A given the information set Θ_t. Since it is based on lag relations inherent in time-series data, temporal Granger causality has little to say about contemporaneous causation. Further, measures of Granger causality may be spoiled by temporal aggregation. Temporal aggregation can lead to misleading inference of Granger causality (Granger, 1980; Tiao, 1999) and occurs when the frequency of observations, i.e. sampling interval, differs from the natural frequency of the underlying time-series variable. In application, a dynamic causal direction can be established when a causal event is observed ahead of the effect, the cause and effect are ordered in time, and the sampling frequency is sufficient to discern the cause and the effect. There should be no contemporaneous relationship between cause and effect if the sampling frequency is observed at the natural frequency (Granger, 1980, 1988). However, with exception of high frequency financial data, it is rare to have no, or very small, temporal aggregation bias. Hence, contemporaneous causality observed under a particular time interval may result from temporal aggregation.[3] Researchers propose to link the concept of Granger causality at the natural

[1] Department of Justice (DOJ) and the Federal Trade Commission (FTC) issued 'Horizontal Merger Guidelines' on 2 April 1992 and revised on 8 April 1997. It classifies the market unconcentrated if the value of the HHI is below 1000, moderately concentrated when the HHI is between 1000 and 1800, and highly concentrated when the HHI is above 1800.

[2] GIPSA (2008) defines captive supply as livestock that are owned or fed by a packer, livestock that are procured by a packer through a forward contract or marketing agreement that has been in place or livestock that are otherwise committed to a packer, for more than 14 days prior to slaughter.

[3] Granger (1988) suggests that the missing variable also could be a source of contemporaneous causality under time interval. However, it is hard to identify what missing variables exist.

frequency with contemporaneous causality in the time aggregation process (Swanson and Granger, 1997; Breitung and Swanson, 2002).

Granger (1980) discusses 'prima facie apparent instantaneous causality in mean' and defines x_{t+1} instantaneous Granger causes y_{t+1}, given the current information set Θ_t, if $E(y_{t+1}|x_{t+1}, \Theta_t) \neq E(y_{t+1}|\Theta_t)$, where $E(\cdot)$ is the expectation operator. Granger (1980) suggests that extra structure is needed to possibly uncover instantaneous causality. Swanson and Granger (1997) introduce graphical methods into contemporaneous causal ordering of Vector Autoregressive (VAR) models. Pearl (2000) and Spirtes *et al.* (2000) develop DAGs utilizing conditional probabilities and graph theory to identify contemporaneous causality. DAGs are advocated by several researchers and have been used in a number of different fields (Swanson and Granger, 1997; Demiralp and Hoover, 2003; Park *et al.*, 2008).

Out-of-sample Granger causality tests for dynamic causality

In-sample Granger causality tests that use all observations for forecasting risk over-fitting the data and can lead to spurious prediction and biased test results. To avoid the potential over-fitting problem, following Granger (1969), a number of studies implement out-of-sample Granger causality tests (Amato and Swanson, 2001; Clark and McCracken, 2001; Corradi and Swanson, 2002; Masih and Masih, 1996).

Following Amato and Swanson (2001) we implement out-of-sample Granger causality tests in a multivariate system represented by a Vector Error Correction Model (VECM). We first examine whether the inclusion of series X_{jt} facilitates predicting X_{it} better for $i \neq j$ given other series. We estimate two VECMs indicated by the superscript m in Equation 1: (a) the unrestricted full model includes all relevant variables ($m = u$) and (b) the restricted models exclude one specific variable from the unrestricted full model ($m = r$)

$$\Delta X_t^m = \Pi^m X_{t-1}^m + \sum_{i=1}^{k-1} \Gamma_i^m \Delta X_{t-i}^m + \mu^m + \varepsilon_t^m \quad \text{for } t = 1, \ldots, T \tag{1}$$

where Δ is a first-order difference operator such that $\Delta X_t^m = X_t^m - X_{t-1}^m$, Π^m is a $p^m \times p^m$ coefficient matrix indicating long-run relationships among variables, and Γ_i^m is also a $p^m \times p^m$ coefficient matrix measuring the short-run effect of ΔX_{t-i}^m on ΔX_t^m, and ε_t^m is a $p^m \times 1$ vector representing multivariate independent, identical sequence with mean zero and covariance matrix Σ^m. Given that $p^u = p$ for the unrestricted models, we have $p^r = p - 1$ for the restricted model with X_t^r excluding one particular variable from X_t^u.

The out-of-sample Granger causality test is conducted as follows. First, we derive a total of $T - R$ one-step-ahead forecasts $\hat{X}_{it}^m$ for $t = R+1, R+2, \ldots, T$ based on the unrestricted ($m = u$) and restricted ($m = r$) models, where the first R observations are used to get the first one-step-ahead forecast $\hat{X}_{i,R+1}^m$. We then calculate forecast errors $e_{it}^m = X_{it}^m - \hat{X}_{it}^m$ for both the unrestricted and restricted models. We define X_{jt} as Granger causing X_{it} if e_{it}^u is smaller than e_{it}^r or if the unrestricted full model including X_{jt} results in more accurate forecasts than the restricted model. Finally, we examine whether one model, either the unrestricted or restricted model, statistically forecasts better than the other. Based on the Mean Squared Forecasting Errors (MSFEs) criterion suggested by Amato and Swanson (2001), we employ the modified Diebold–Mariano (DM) test (Harvey *et al.*, 1997) for equal forecasting performance in which the null hypothesis is $d_t = e_{ut}^2 - e_{rt}^2 = 0$. The corresponding DM test statistic is

$$DM = (\hat{V}(\bar{d}))^{-0.5} \bar{d} \tag{2}$$

where $\bar{d}$ is the sample mean of d_t, $\hat{V}(\bar{d})$ is the Newey–West heteroscedacity and autocorrelation consistent estimator of the sample variance of d_t. Since the distribution under the null hypothesis is nonstandard, we use the simulated critical value developed by Clark and McCracken (2001) for DM tests.

Contemporaneous causality test using DAGs

DAGs are pictures using arrows and vertices (variables) to represent the contemporaneous causal flow among or between a set of variables based on observed correlation and partial correlations (Pearl, 2000; Spirtes *et al.*, 2000). DAGs can be used to represent conditional independence as implied by the recursive product decomposition

$$\Pr(v_1, v_2, v_3, \ldots, v_n) = \prod_{i=1}^{n} \Pr(v_i | pa_i) \tag{3}$$

where Pr is the probability of vertices $v_1, v_2, v_3, \ldots, v_n$ and pa_i is the realization of some subset of the variables that precede v_i in order $(v_1, v_2, v_3, \ldots, v_n)$. For further discussion of DAGs, see Spirtes *et al.* (2000) and Bessler and Yang (2003) incorporate the notion of d-separation into an algorithm for building DAGs. We use the Greedy Equivalent Search (GES)

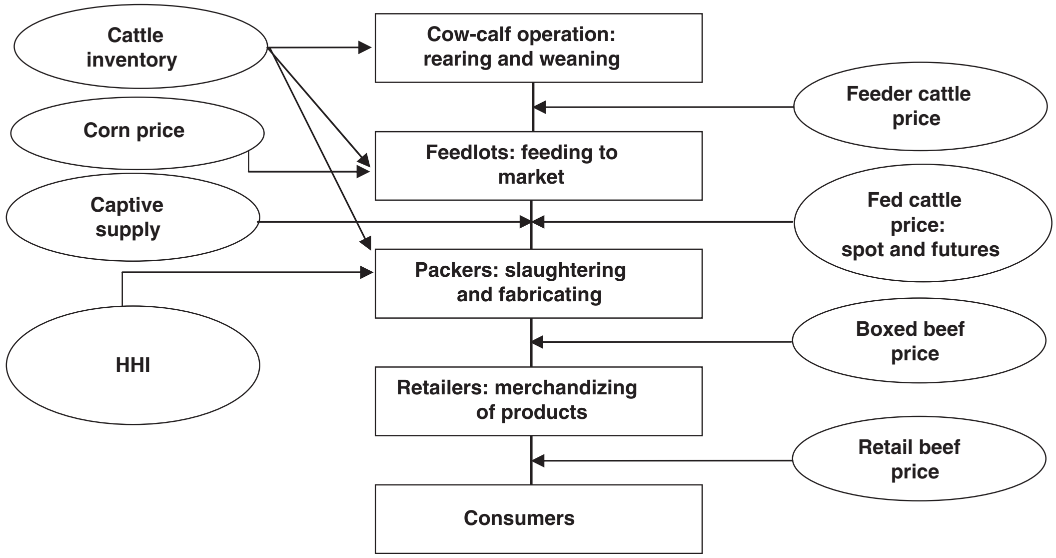

Fig. 1. Overview of the US beef supply chain

algorithm to generate DAGs (see details in Chickering, 2002, pp. 520–4).[4]

III. Overview of the US Beef Supply Chain and Data Descriptions

As shown in Fig. 1, the US beef supply chain is characterized by multiple production stages. Cow-calf and background operations, where rearing and weaning take place, are first-stage producers providing feeder steers and heifers weighing more than 500 pounds. Feedlots (feeding operations) purchase feeder cattle from cow-calf and background operations and feed animals high-energy rations to finish them as fed cattle weighing approximately 1200 pounds. These fed cattle are purchased by beef packers. Beef packers slaughter and fabricate the finished fed cattle in their packing plants, and produce boxed (or wholesale) beef and other products as their final output. Retailers, including supermarkets, grocery stores, fast-food outlets and restaurants at the top of the supply chain sell beef to consumers.

In recent years, the US beef supply chain has become more concentrated at both the processor and retail levels. In addition, the industry has made increasing use of contracts to coordinate transactions between tiers throughout the supply chain. These changes offer potential efficiency gains from improved coordination and information sharing and/or control. However, the increasing use of captive supply along with high concentration among packers has also raised concern about competitiveness and possible market manipulations by packers in spot market procurement (Love and Burton, 1999; Xia and Sexton, 2004). Overall, the literature offers mixed results on the relationship between captive supply and fed cattle spot price, and is silent about the causal direction between the two variables even though a natural or implicit causal direction can be inferred. Understanding causal linkages among transaction prices and various sector driver variables at different tiers in the US beef supply chain has rich policy implications for both regulators and participants in the supply chain. Such understanding offers a first step in understanding how recent changes in concentration and increased contract coordination may be influencing supply chain participants.

We use monthly data for nine variables representing important information and decision points for participants in the decentralized multi-echelon supply chain of the US beef industry (see Fig. 1). Data are from January 1988 to August 2005, and include: captive supply, cattle inventory, feeder cattle price, fed cattle spot price, boxed beef price, retail beef price, fed cattle futures price, corn price and the packer HHI. All variables except captive supply and fed cattle futures price are collected from the Red Meat Yearbook published by Economic Research Service (ERS) of United States Department of Agriculture (USDA).

Captive supply (CAPT), measured as the percentage of total slaughter cattle procured through captive

[4] GES algorithm has several advantages over PC algorithm. It does not require as strong assumptions as PC algorithm (causal sufficiency, Markov condition and faithfulness). An appropriate significance level is not required in GES algorithm.

supply arrangements by the four largest packing firms, is obtained from GIPSA. Captive supply is used to represent the degree of quasi-vertical integration in the cattle industry. Based on semi-annual cattle inventory data published by ERS in January and July we construct monthly cattle inventory (INVT) by subtracting monthly cattle slaughter from the previous cattle inventory and adding the monthly calf crop.[5] Cattle inventory provides information on current and future beef production. Although the cyclical influence of cattle inventory is a primary factor determining beef supply that affects all live cattle production stages in the supply chain, it also has a large effect on the overall cattle industry giving it its cyclical nature. We use feeder steer price (Oklahoma City, 750–800 lb, medium #1) to represent feeder cattle prices (FEEP), wholesale boxed beef cutout value (Choice 1–3, Central US, 600–750 lb) for boxed beef prices (BOXP), USDA all-fresh retail beef price from the cattle fax for retail beef prices (REBP), and Corn #2 Yellow, Central Illinois for feed corn prices (CORP). Fed cattle spot price (FEDP) is a weighted price index calculated using a Tornquist index based on prices and quantities of steers and heifers (Choice 2–4, Nebraska, 1100–1300 lbs). Fed cattle constitute a major input in packer production and account for most of the production costs. Fed cattle futures prices (FUTP) traded in Chicago Mercantile Exchange (CME) are obtained from DataStream, an electronic database system providing historical financial data sets. The HHI, calculated as the sum of the squared market shares of individual firms reported by GIPSA, is used as a measure for packer concentration.

Figure 2 plots these nine variables during the study period (1988:01–2005:08). We use logarithmic transformation of all the nine series for the analysis.

IV. Empirical Results

Diagnosis testing

Many economic and financial time-series are characterized by a unit root (Hendry and Massmann, 2007). The Dickey–Fuller (DF) and Philip–Perron (PP) tests are commonly used to test the unit root hypothesis. These tests are, however, biased in the presence of omitted structural breaks (Zivot and Andrews, 1992), leading to forecast failure (Hendry and Massmann, 2007). An alternative is the Zivot and Andrews (ZA) unit root test that allows for one possible shift in mean, trend or both. The null hypothesis in the DF type tests (DF, PP and ZA) is of a unit root (nonstationary), which is accepted unless there is strong evidence against it. The DF type tests have low power against the alternative hypothesis (Diebold and Rudebusch, 1991; DeJong *et al.*, 1992). Kwiatkowski *et al.* (1992) developed the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) tests of the null hypothesis of stationarity either around a level or around a linear trend. We employ both DF type tests and KPSS tests and report the results in Table 1.

The DF, PP and ZA tests fail to reject the null hypothesis that the data series (in logarithm) in level contain a unit root at the 5% level of significance, except captive supply (CAPT) and cattle inventory (INVT) under all three tests (DF, PP and ZA), futures price (FUTP) and corn price (CORP) under some tests. The same tests are applied to the first order differences of each series. In each case, the unit root hypothesis is rejected at the 5% level of significance. The KPSS tests reject the null hypothesis of stationarity in level, but fail to reject stationarity in first order difference. Based on results reported in Table 1, we conclude that all series are nonstationary in levels but stationary in first order differences, suggesting the use of a VECM to model all series representing the US beef industry.

Different approaches are available to determine the optimal lag length (k) and the cointegration rank (r) for a VECM. The conventional approach is to sequentially determine lag length using information matrices, and then determine the rank of cointergration vectors based on Johansen trace tests. Given the fact that the true model is rarely known, this procedure involves trade-offs between model parsimony and fit (Wang and Bessler, 2005). Phillips (1996) proposed a model selection method based on information criteria to jointly determine k and r. Model selection methods have been implemented in several studies (Phillips and McFarland, 1997; Aznar and Salvador, 2002; Baltagi and Wang, 2007; Park *et al.*, 2008). Model selection methods relieve researchers from the arbitrary choice of an appropriate significance level in contrast with formal hypothesis testing used in system-based Likelihood Ratio (LR) tests. Chao and Phillips (1999) and Wang and Bessler (2005) provide simulation evidence to show the model selection methods based on information criterion give at least as good fit as system-based LR tests. Baltagi and Wang (2007) find model selection methods produce the same results as system-based

[5] Even though semi-annual cattle inventory data may reduce variation of the constructed monthly cattle inventory variable, to great extent, the monthly cattle slaughter and the monthly calf crop preserve variation of cattle inventory.

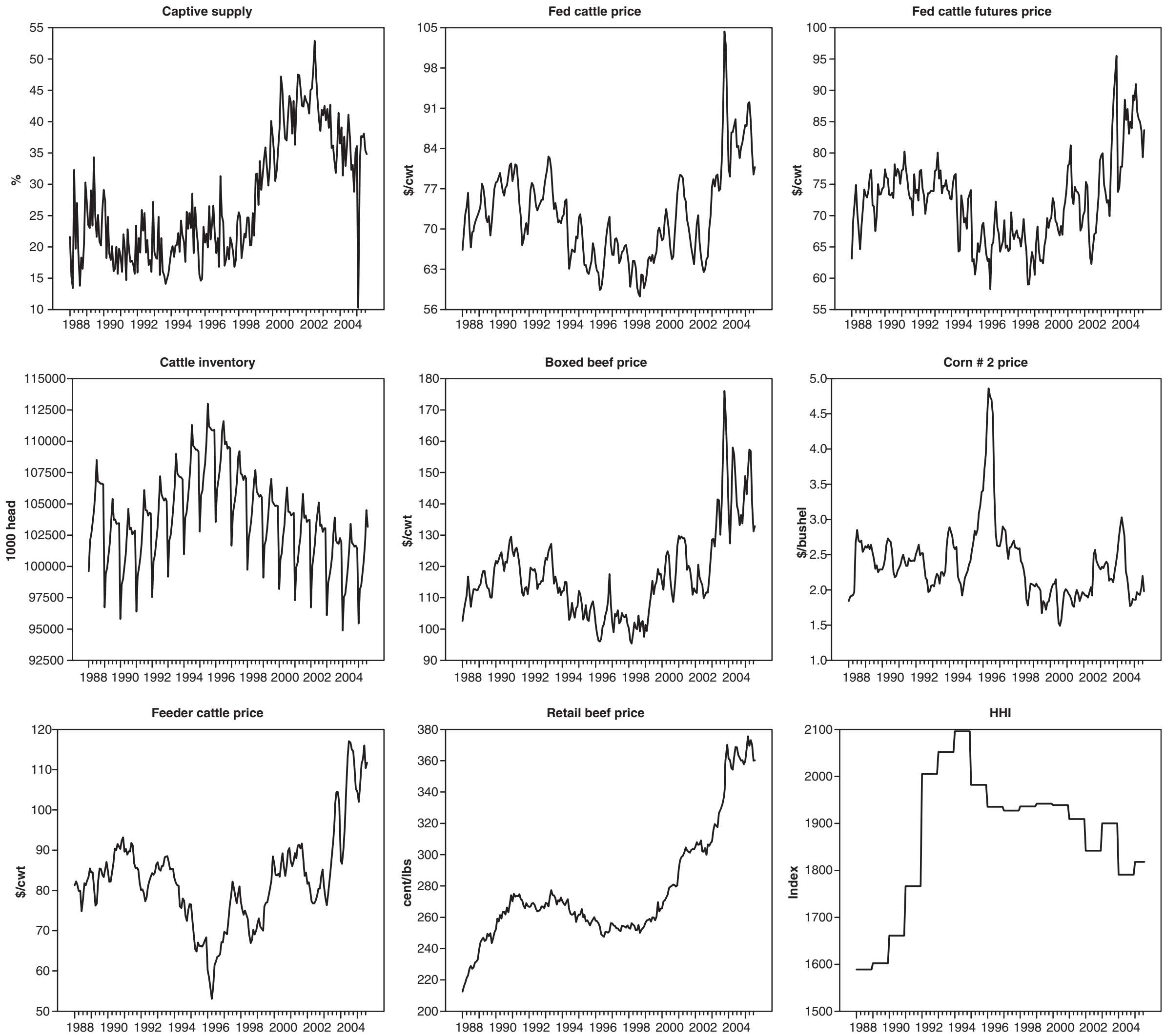

Fig. 2. Nine important variables along the US beef supply chain (1988:01–2005:08)

LR tests in 70% of 165 published data sets. Using the entire data, results based on both methods are consistent – the optimal lag length is two and the rank of cointegration vectors is five.

Results of structural break tests

Since causalities may respond to exogenous shocks or change through time, we first identify possible structure changes using time-varying cointegration estimation (Juselius, 2006). As shown in Fig. 3, normalized trace test results suggest the presence of time-varying cointegration relationships among variables in the supply chain. Under rolling cointegration tests, the null hypotheses of no cointegration ($r = 0$) and at most one cointegration vector ($r \leq 1$) are rejected over the whole sample periods since the normalized trace test statistics are greater than one. Based on test results for $r \leq 2$ and $r \leq 3$, minor regime changes in early 2001 and 2003 are detected. We speculate two events contribute to instability of the cointegration, the Livestock Mandatory Price Reporting (LMPR) Act made effective in April 2001 to stimulate competition in livestock markets including fed cattle market, and the Canadian and US BSE (Bovine Spongiform Encephalopathy) discoveries in 2003. The most striking evidence for instability of cointegration relationships detected in the null hypothesis of $r \leq 3$ suggests a remarkable structural change between the late 1996 and early 1997, which coincides with an apparent turnaround of the US cattle production cycle. The US cattle production cycle typically occurs every 10 to 12 years, which consists of 6–7 years of expanding, 1–2 years of consolidation, and 3–4 years of declining before the next cycle begins (Mundlak and Huang, 1996). The US cattle cycle experienced a contraction phase after the peak of cattle inventory in January

Table 1. Tests for nonstationarity of data series

Data series	DF test Level	DF test Diff.	PP test Level	PP test Diff.	ZA test[a] Level	ZA test[a] Diff.
Null hypothesis for DF, PP and ZA tests: containing a unit root (nonstationary)						
CAPT	−4.05**	−23.12**	−3.21*	−28.87**	−5.19*	−11.82**
INVT	−5.32**	−17.65**	−5.38**	−17.93**	−7.28**	−17.65**
FEEP	−1.02	−10.19**	−1.43	−9.91**	−3.61	−8.86**
FEDP	−2.41	−9.59**	−2.73	−9.09**	−4.58	−10.56**
BOXP	−2.40	−11.19**	−2.39	−10.83**	−3.96	−9.82**
REBP	−0.60	−13.91**	−0.63	−13.91**	−3.25	−14.60**
FUTP	−3.70**	−14.68**	−3.51**	−15.10**	−4.78	−11.07**
CORP	−2.53	−10.28**	−3.17*	−10.23**	−5.20*	−7.80**
HHI	−2.07	−14.46**	−2.07	−14.46**	−4.68	−14.96**
Null hypothesis for KPSS tests: stationary						
Level	$L=0$	$L=1$	$L=2$	$L=3$	$L=4$	$L=5$
CAPT	1.73**	1.02**	0.73**	0.57**	0.48**	0.41**
INVT	2.14**	1.22**	0.89**	0.72**	0.62**	0.56**
FEEP	3.16**	1.61**	1.09**	0.84**	0.68**	0.58**
FEDP	2.90**	1.49**	1.03**	0.80**	0.66**	0.59**
BOXP	3.25**	1.68**	1.16**	0.90**	0.74**	0.63**
REBP	3.68**	1.84**	1.24**	0.93**	0.75**	0.63**
FUTP	2.76**	1.48**	1.04**	0.83**	0.69**	0.60**
CORP	1.01**	0.52**	0.36**	0.28**	0.24**	0.23**
HHI	4.00**	2.02**	1.36**	1.03**	0.83**	0.70**
Difference	$L=0$	$L=1$	$L=2$	$L=3$	$L=4$	$L=5$
CAPT	0.01	0.02	0.03	0.04	0.04	0.05
INVT	0.01	0.01	0.01	0.01	0.02	0.02
FEEP	0.06	0.04	0.04	0.04	0.04	0.04
FEDP	0.04	0.03	0.03	0.03	0.04	0.04
BOXP	0.04	0.03	0.03	0.04	0.04	0.05
REBP	0.02	0.02	0.02	0.02	0.03	0.03
FUTP	0.03	0.03	0.03	0.03	0.04	0.05
CORP	0.05	0.04	0.03	0.03	0.03	0.03
HHI	0.07	0.07	0.07	0.07	0.07	0.07

Notes: The critical values at the 5 and 1% significance levels are −2.88 and −3.47 for both DF tests and PP tests; −4.80 and −5.43 for ZA tests; and 0.15 and 0.22 for KPSS tests.
[a]The results of ZA tests reported pertain to a potential structural break occurring in intercept, which are consistent if allowing for break to occur in trend or both intercept and trend.
* and ** indicate 5 and 1% significance levels, respectively.

1996 (103.5 million head).[6] The cattle cycle can greatly contribute to the transformation of market structure (Mathews *et al.*, 1999). Grain shocks caused by a Midwestern draught between the late 1995 and early 1996 may have amplified the cattle-cycle related market influences. The severe draught caused a remarkably high spike in corn price in 1996, which clearly affected profits throughout the beef supply chain. Similarly, under the recursive cointegration tests, two regime changes were suggested, one between the late 1995 and early 1997 and another one in early 2002 that was likely induced by the LMPR Act.

To validate the structural break suggested by the cointegration trace tests, we adopt an advanced approach recently proposed by Qu and Perron (2007).[7] Based on Hawkins (1976) and Bai and Perron (1998, 2003), Qu and Perron (2007) propose procedures to deal with issues related to estimation, inference and computation when multiple structural changes occur at unknown dates in a system of equations. Their methods not only allow changes to occur in the regression coefficients and/or the covariance matrix of the errors, but also allow arbitrary restrictions on these parameters, which

[6] USDA reports that cattle inventory decreased to 95 million head in January 2004 (cyclical low), but it has been expanded since 2005 reaching 97 million head in January 2007.
[7] We thank one anonymous reviewer for challenging us to further valid the structure breaks suggested by the cointegration trace tests.

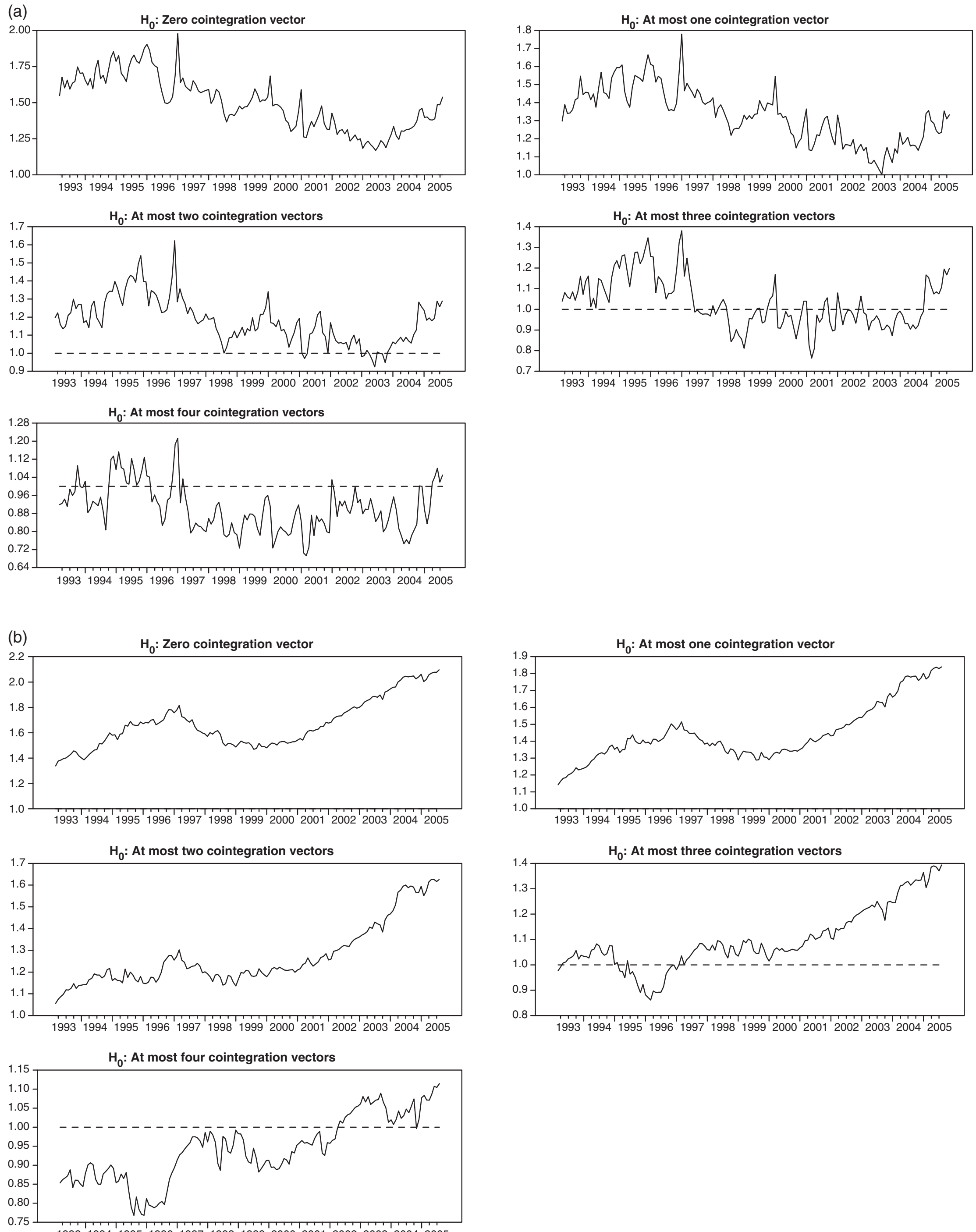

Fig. 3. Normalized trace tests of the time-varying cointegration estimation. Normalized trace tests based on the (a) rolling cointegration vectors; (b) recursive cointegration vectors

permits the analysis of partial structural change models, common breaks occurring in all equations or breaks occurring in a subset of equations. Using Qu and Perron's approach we identify two structural breaks. The most significant structure break was in December 1996 that is consistent with what is suggested by the cointegration trace tests. The minor structural break was in December 2000 that was almost 1 year earlier than what is suggested by the cointegration tests.

We argue there was at least one significant structural break corresponding to the 1996 grain shock and the turnaround of the US cattle cycle. For the minor structural breaks, whether it was in the late

2000 or early 2002, we do not have sufficiently long series to analyse the post-break periods. Thus, we divide the entire sample period into two sub-periods according to the significant regime change between the late 1996 and early 1997: pre-break periods (1988:01–1996:10) and post-break periods (1997:03–2005:08). We exclude the 4-month interval (1996:11–1997:02) from the analysis as transition periods, since the contemporaneous causal orderings are sensitive to including these periods.

We also conduct a recursive innovation accounting analysis and Box-M and Jennrich tests to validate the structural change.

(1) Variance Decompositions (VDs) and Impulse Response Functions (IRFs): VDs partition the variance of the forecast error of a certain variable into proportions attributable to innovations in each variable in the system including its own. VDs provide an indication to gauge the relative strength of Granger-causal chain or degree of erogeneity amongst the variables beyond the sample period (Masih and Masih, 1996). The IRFs trace the dynamic response of a variable due to a one-period SD shock to another variable. If there is a structural change, we should expect changes in both VDs and IRFs.

Figure 4(a) presents results of the impacts of captive supply on the variance of forecast error of spot market prices for a 12-month horizon. The vertical axis in Fig. 4(a) represents the percent of the variance in forecast error of each spot market price that can be explained by captive supply. The influence of captive supply is generally weaker on the variance of forecast error of feeder cattle price but stronger on that of retail and boxed beef prices in the post-break periods than in the pre-break periods. The vertical axis in Fig. 4(b) presents the response of spot market prices to a one-time shock of captive supply. As shown in Fig. 4(b), an increase in captive supply procurement generally decreases fed cattle spot market prices in the majority of the pre- and post-break periods. In most periods, it appears that captive supply procurement might have been used as a strategic instrument to reduce fed cattle prices (see, e.g. Love and Burton, 1999; Xia and Sexton, 2004). However, in the 1999/2000 and 2001 periods, this does not seem to be the case. In this period, cattle inventory is falling and captive supply procurement is rapidly rising. It appears that packers may have transitioned to increased use of captive supplies as a more important way to ensure an adequate supply of fed cattle. As a result, procurement through captive supply mechanisms became so large in relation to total cattle availability that any changes in captive supply quantities were directly transmitted to the spot market fed cattle price. It further appears that the effects of changes in captive supplies had direct spillover effects on feeder cattle price, boxed beef price and retail price. Interestingly, in the periods directly following 2001, packers reduced the proportion of cattle purchased through captive supply channels and the historic relationship of increased use of captive supply procurement inversely impacting spot market fed cattle price was re-established. Overall, the innovation accounting analyses between the before- and after-break periods supports the 1996–1997 structural change.[8]

(2) Box-M and Jennrich tests for the Homogeneity of Matrices: If there is a structural change, the two covariance matrices or two correlation matrices based on estimated VECMs in the pre- and post-break periods will statistically differ from each other. We employ both the Box-M test (Box, 1949) for the equality of the two covariance matrices and the Jennrich test (Jennrich, 1970) for the equality of the two correlation matrices.[9,10] We find that the statistic for the Box-M test (262.36) exceeds the

[8] Due to the space limit we only present the impact of captive supply on spot prices. Other recursive innovation analyses are available upon request.

[9] When the sample size is small, the modified Box-M test statistic for the homogeneity of two covariance matrices is

$$M = \gamma \sum_{i=1}^{2} (n_i - 1) \log \left| \frac{\Omega_u}{\Omega_{ui}} \right|$$

where

$$\Omega_i = \frac{n_i}{n_i - 2}\Omega \quad \text{for } i = 1 \text{ or } 2, \quad \Omega = \frac{\Omega_1 n_1 + \Omega_2 n_2}{n_1 + n_2}, \quad \gamma = 1 - \frac{2s^2 + 3s - 1}{6(s+1)}\left(\sum \frac{1}{n_i - 1} - \frac{1}{n_1 + n_2 - 2}\right)$$

Note that n_i is number or observations to derive sample covariance matrix Ω_i and s is the dimension of the covariance matrix. The Box-M test statistic is asymptotically distributed as a chi-square distribution with the degree of freedom $s(s+1)/2$.

[10] Jennrich (1970) propose a chi-square test for the homogeneity of covariance or correlation matrices. The test statistic for the homogeneity of two correlation matrices (Σ_1 and Σ_2) is $\frac{1}{2}\mathrm{tr}(Z^2)$ where $\mathrm{tr}(\cdot)$ is a trace operator, $Z = c^{1/2}\bar{\Sigma}^{-1}(\Sigma_1 - \Sigma_2)$, $c = n_1 n_2/(n_1 + n_2)$, and $\bar{\Sigma} = (n_1\Sigma_1 + n_2\Sigma_2)/(n_1 + n_2)$. The Jennrich test statistic is asymptotically distributed as a chi-square distribution with the degree of freedom $s(s-1)/2$.

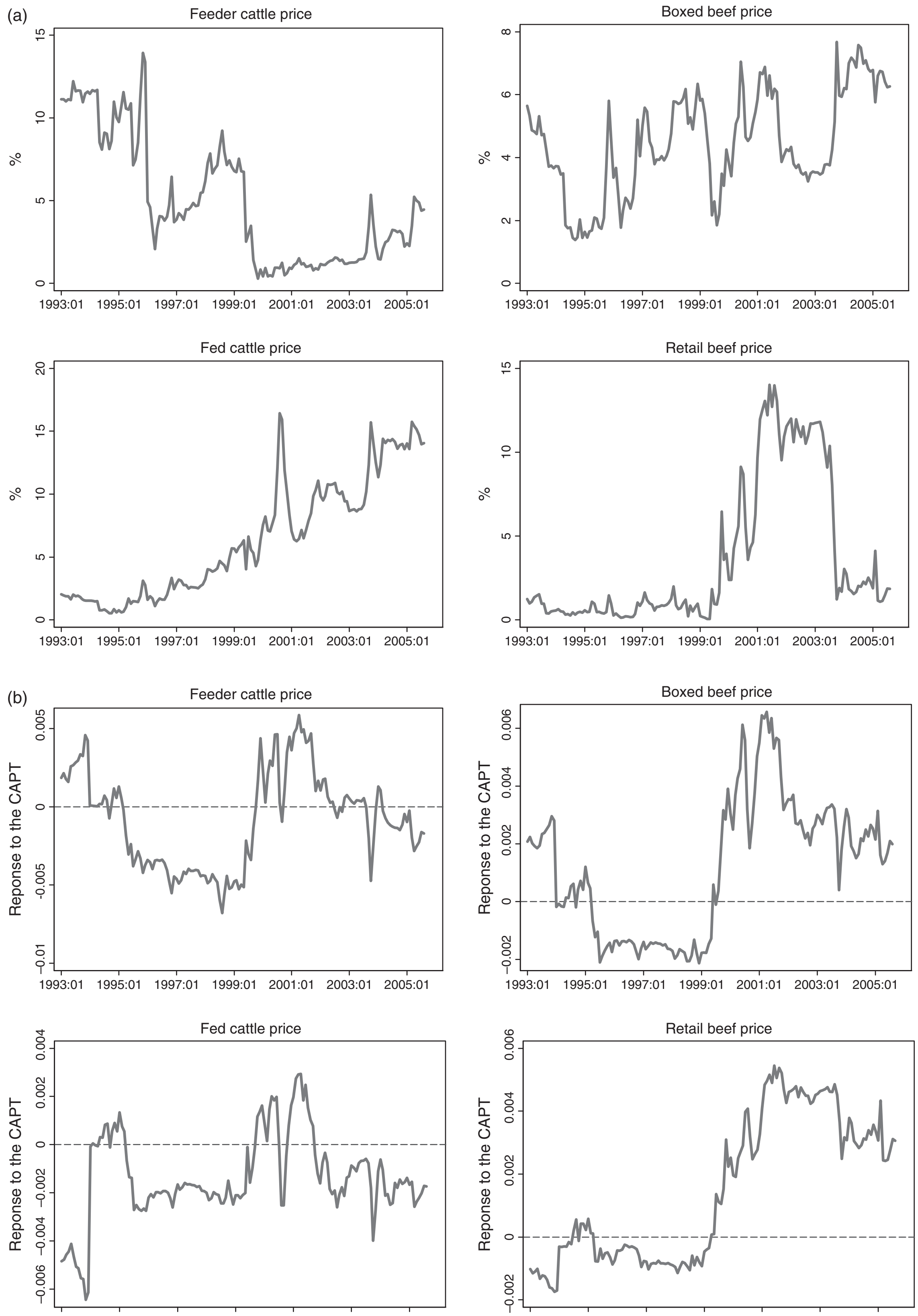

Fig. 4. Recursive innovation accounting analysis at the 12-month horizon. (a) Impacts of captive supply on the variance of forecast error of spot prices; (b) IRFs of four spot prices responding to the one-time shock of captive supply

Table 2. Out-of-sample temporal Granger causality tests

	CAPT	*INVT*	*FEEP*	*FEDP*	*BOXP*	*REBP*	*FUTP*	*CORP*	*HHI*
Pre-break periods									
CAPT	–	0.474**		0.752**		0.535**			
INVT		–		−0.755	−0.796				0.499**
FEEP	0.742**		–	−0.678	−0.751		−1.945	−1.464	
FEDP		−0.850	−0.504	–		−1.511			0.039
BOXP		−0.623	−0.365		–	−0.623	−1.369	0.66	
REBP				−1.169	−1.223	–			
FUTP	1.341**		−0.309	1.650**	−0.306	0.568**	–	0.126	0.0143
CORP	0.695**	0.810**	−0.506					–	
HHI								0.885**	–
Post-break periods									
CAPT	–								
INVT	0.041	–		0.097*			−0.101	−0.060	
FEEP		−0.051	–		−0.186		0.033		
FEDP	0.332*	−0.047	0.325*	–		−0.006		−0.009	0.020
BOXP	0.002	−0.144		0.008	–	−0.034		−0.005	0.016
REBP	0.065		−0.069		0.153*	–		−0.025	0.009
FUTP			0.129*	0.164*			–		
CORP								–	
HHI									–

Notes: No entry on any off-diagonal cell represents cases that an unrestricted model has a larger MSFE than a restricted model. The null hypothesis is that each series in the first row does not Granger cause any particular series in the first column. According to Clark and McCracken (2001), the critical values (MSE-T test) of the DM test are 0.397 at the 95% confidence level and 0.096 at 90% confidence level.
* and ** indicate that the null is rejected at the 10 and 5% significance levels, respectively.

critical value ($\chi^2(45) = 71.17$), and the statistic for the Jennrich test (135.44) also exceeds the critical value ($\chi^2(36) = 61.58$) at the 1% significance level. Hence, the two variance matrices or correlation matrices in the pre- and post-break periods differ from each other, supporting the structural change.

We then examine casualty before and after the break detected in the late 1996 and early 1997.

Results of Granger dynamic causalities

For the pre-break periods, we first determine the optimal lag length (k) and the cointegration rank (r) for the unrestricted full model and for each of the restricted models. For each model, we calculate one-step-ahead forecasts and the corresponding forecast error series after fitting a VECM. In the case of the unrestricted full model, we use the first 60 monthly observations (1989:01–1993:12) to obtain one-step-ahead forecasts for 1994:01 of the nine series, the first 61 observations (1989:01–1994:01) to obtain the forecasts for 1994:02, and so forth until all pre-break periods are exhausted. Consequently, we obtain 34 one-step-ahead out-of-sample forecasts (1994:01–1996:10) and nine forecast error series with dimension of 34-by-l for the unrestricted model. Similarly, we obtain 72 forecast error series (nine restricted models with eight variables) for the nine restricted models. In total we have 81 forecast error series from the restricted and unrestricted models to conduct multivariate out-of-sample Granger causality tests. By comparing the MSFEs between the unrestricted and restricted models, we find 46% (33 out of 72 cases) of the unrestricted models have lower MSFEs and, therefore, more accurate forecasts than the restricted model. The difference of the MSFEs between the restricted and unrestricted models is quite small, a statistical DM test for the equal forecasting errors is conducted based upon Equation 2. Following the same procedure applied to the post-break periods we conduct Granger causality tests for the post-break periods (1997:03–2005:08).

Table 2 summarizes Granger causality test results in the pre- and post-break periods. The null hypothesis is that each series in the first row does not Granger-cause any particular series in the first column given inclusion of other series in the first column. Eleven statistically significant out-of-sample Granger causalities are found in the pre-break periods, and only six significant Granger causalities are found in the post-break periods.

We present the direction of Granger causalities before- and after-break periods in Fig. 5(a) based on

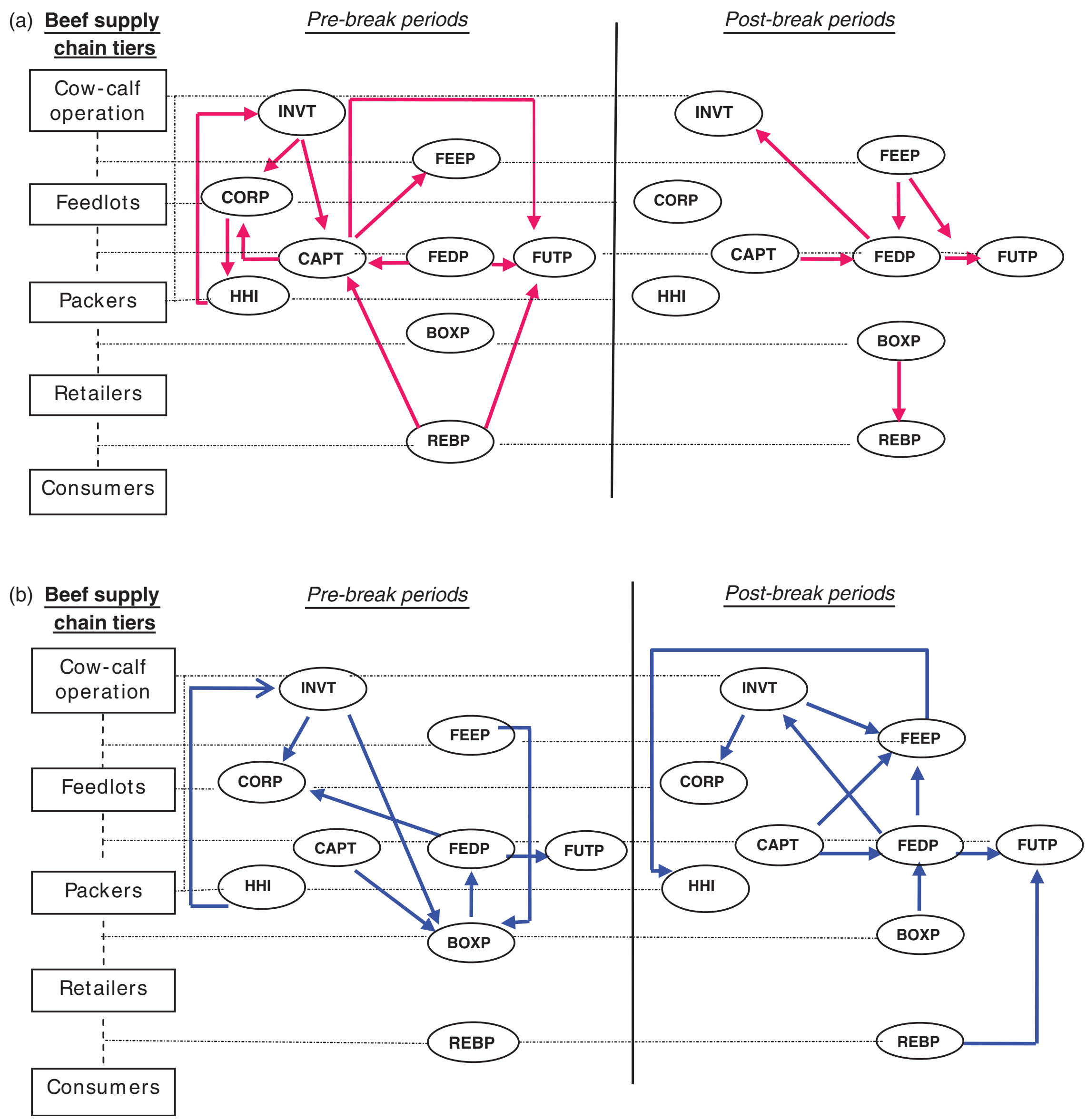

Fig. 5. Temporal and contemporaneous causal relationships along the US beef supply chain before and after the 1996–1997 structural change (a) dynamic Granger causalities; (b) contemporaneous DAG causalities

the results in Table 2. Overall, the temporal (dynamic) causal relations among variables in the US beef supply chain become much weaker after the structural change. In the pre-break periods, it appears that captive supplies are more connected to other variables than in the post-break periods. Moreover, in the pre-break periods, the direction of causality appears to be mainly toward captive supply while in the post-break periods the direction of causality is from captive supply to fed cattle price. In the pre-break periods it appears that packers may be reacting to signals from the retail and feeder levels when they make captive supply procurement decisions. In turn, these decisions dynamically influence important feeder input prices for feeder cattle and corn. In the post-break periods, only one important dynamic connection indicates packers may be directly using captive supply to influence fed cattle prices. Furthermore, in the post-break periods, temporal causalities are mainly from upstream to downstream or in the same tier of the supply chain with an exception that fed cattle spot price Granger causes cattle inventory. While the causalities embedded in the pre-break periods do not have clear directional pattern along the supply chain tiers, it seems clear that the numerous dynamic linkages suggest poor coordination and inefficiencies in the beef supply chain. Further, it appears in the post-break periods that the decentralized multi-echelon beef supply chain experienced significant improvements in coordination since few dynamic causalities are indicated in that time horizon. In all periods, the direction of causality is always toward futures price. This finding suggests that futures price results from market information but does not drive decisions made along the supply chain.

Results of DAG contemporaneous causalities

Figure 5(b) shows two DAGs, generated using TETRAD IV's GES algorithms, representing the direction of contemporaneous causal flows among variables in the pre- and post-break periods. Comparison of the two DAGs suggests that causalities change after the structural break between late 1996 and early 1997. A striking finding is that more contemporaneous causal relationships appear to be present in the post-break period, which implies that information flow is quicker and/or more effective within the beef supply chain in recent times than in times past. This finding complements the dynamic causal analysis that indicates the reverse. The direction of causalities appears to shift from upstream to downstream causal flows in the pre-break period to upstream from downstream causal flows in the post-break period. This means that before the structural break, most information in the supply chain appears to flow downstream, from cow-calf operations to packers. After the structural break, most information in the supply chain appears to flow upstream from retailers and packers to feeders and cow-calf operators.

Further, before the structural break, it appears that price discovery in the supply chain occurred in boxed beef pricing where information from feeder steer prices, cattle inventory and captive supply comes together to determine boxed beef price, the most endogenous variable. After the structural break, it appears that price discovery in the supply chain occurred in feeder steer pricing where information from fed cattle price, captive supply and cattle inventory comes together to determine feeder steer price, the most endogenous variable. This reversal in information flow may have resulted from increased concentration at both the packer and retail levels and from greater use of contracts by packers in recent times.

Improved coordination and control in the post-break periods, reflected through fewer dynamic and more contemporaneous causal relationships in the post-break when compared to the pre-break periods, may also be attributed to increased concentration at both the packer and retail levels and increased use of contracts. In particular, captive supply only indirectly causes fed cattle spot price in the pre-break periods, but it appears to directly cause feeder cattle price and fed cattle spot price in the post-break periods. In other words, captive supply appears to exhibit an increased contemporaneous influence on prices along the supply chain, which supports the argument that the use of noncash procurement by packers leads to pressure on spot market price as several previous empirical studies found (Schroeder *et al.*, 1993; Ward *et al.*, 1998; Conner *et al.* 2004). In recent periods, we observe that retail beef price causes fed cattle futures price but retail beef price is independent of other variables in the pre-break periods. This may be evidence of increasing power and influence of retailers in meat pricing in the post-break period.

Another interesting finding in the contemporaneous causalities analysis is that upstream cattle producers seem to exert less influence on the supply chain in the post-break periods than in the pre-break periods. In the pre-break periods, cattle inventory appears as a causal variable in both corn price and boxed beef price determination, suggesting that cattle producers have a direct and contemporaneous influence on downstream pricing of meat. In the post-break periods, variables associated with cattle producers are influenced by other upstream variables and downstream variables, but upstream cattle production related variables have no contemporaneous influence on downstream variables. This suggests that in the post-break periods, cattle producers react to information, but do not have a controlling influence on supply chain decisions.

In the pre-break periods, the HHI for market concentration in the meat packing industry appears to have both dynamic and contemporaneous influences on cattle inventory. In the post-break periods, these causal relations disappear. This result seems counter intuitive. Direct HHI causal results should be interpreted with caution. However, cattle cycles are quite complex and difficult to predict. Overall, the results seem to support the notion that increased concentration at both the packer and retail levels resulted in improved supply chain coordination and a change in direction in the control of decisions from more upstream control in pre-break periods to more down-stream control in post-break periods. Similar to the dynamic causality results, in all periods, the direction of causality is always toward futures price. This finding suggests that futures price results from market information.

V. Conclusions

Employing out-of-sample Granger causality tests and DGAs, this study investigates both dynamic (temporal in Granger sense) and contemporaneous causalities. These two complementary causalities present a better understanding of causal links in a multi-echelon supply chain where no central authority has system level control over optimizing decisions.

The empirical application to the US beef supply chain investigates relationships among prices and selective sector driving variables throughout the supply chain. Results suggest the following: first, based on the time-varying trace test results and the knowledge of historical events in the US beef supply chain, we detect a significant structural change between late 1996 and early 1997 that corresponds to a weather-induced grain shock and a turnaround of cattle inventory cycle. The 1996–1997 structural change is supported by Qu and Perron's tests and Box-M and Jennrich tests as well as by comparison of dynamic recursive impulse responses and forecast error variance decomposition between pre- and post-break periods.

Second, we find that causal relationships in the US beef supply chain changed after the structure change. Overall, temporal causality becomes weaker but contemporaneous causality becomes stronger after the structural break. Stronger contemporaneous causality after the structural break implies that new information or shocks emanating from a particular segment of the supply chain are more quickly and effectively transmitted to the rest of the supply chain in the post-break period compared with the pre-break period. In the post-break periods, dynamic causalities are mainly from upstream to downstream or in the same tier of the supply chain, while contemporaneous causalities indicate information flows upstream from retailers and packers to feeders and cow-calf operators. One might speculate that price discovery occurs in more competitive markets where market influences are more quickly incorporated into price. This point in the supply chain appears to have switched during the period of analysis. In the periods before 1996–1997, price discovery appears to occur in boxed beef pricing. After 1996–1997, price discovery appears to shift to feeder cattle pricing. Further, in the post-break periods, it appears that the cattle production sector is more responsive to rather than responsible for changes occurring elsewhere in the supply chain. We speculate that all of these changes are likely the result of higher industry concentration at the packer and retail levels that facilitates increased use of more effective vertical coordination and contractual arrangements and possibly from implementation of mandatory livestock price reporting that improved fed cattle price reporting.

Third, both temporal and contemporaneous causality results show that captive supply directly causes fed cattle spot price in the post-break periods but only indirectly effects fed cattle price in the pre-break periods. The causal relationship between captive supply and fed cattle spot price supports both theoretical and empirical research that concludes that noncash procurement can affect spot market price.

Clearly, increasing concentration and use of contracts to coordinate production and exchange between different tiers in the US beef supply chain has altered the influence of different players in the system. Overall, it appears that the meat supply chain has become better coordinated and that information flows have become more effective. Further, it appears that control of the supply chain has shifted downstream and that captive supplies exert an important influence on fed cattle cash prices. Improved understanding of causal linkages among the different segments of the US beef supply chain has rich policy implications for both policy makers and market participants. While it remains challenging to uncover causal relationships among variables using non-experimental observational data, the methods available today are allowing applied economists to gain some new understanding. The proposed methodologies can be used to analyse other types of value chains as well as other dynamic systems.

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References

Agricultural Marketing Service (AMS) (2008) The dynamics of change in the US food marketing environment, AMS, Market Services Program (Agricultural Handbook 728-3), USDA. Available at http://www.ams.usda.gov/AMSvl.0/getfile?dDocName=STELPRDC5070995 (accessed 4 May 2010).

Amato, J. D. and Swanson, N. R. (2001) The real-time predictive content of money for output, *Journal of Monetary Economics*, **48**, 3–24.

Awokuse, T. O. (2006) Export-led growth and the Japanese economy: evidence from VAR and direct acyclic graphs, *Applied Economics*, **38**, 593–602.

Aznar, A. and Salvador, M. (2002) Selecting the rank of cointegration space and the form of the intercept using an information criterion, *Econometric Theory*, **18**, 926–47.

Bai, J. and Perron, P. (1998) Estimating and testing linear models with multiple structural changes, *Econometrica*, **66**, 47–78.

Bai, J. and Perron, P. (2003) Computation and analysis of multiple structural change models, *Journal of Applied Econometrics*, **18**, 1–22.

Baltagi, B. H. and Wang, Z. (2007) Testing for cointegrating rank via model selection: evidence from 165 data sets, *Empirical Economics*, **33**, 41–9.

Bessler, D. and Yang, J. (2003) The structure of interdependence in international stock markets, *Journal of International Money and Finance*, **2**, 261–87.

Box, G. E. P. (1949) A general distribution theory for a class of likelihood criteria, *Biometrica*, **36**, 317–46.

Breitung, J. and Swanson, N. R. (2002) Time aggregation and spurious instantaneous causality in multiple time series mode, *Journal of Time Series Analysis*, **23**, 651–65.

Cachon, G. P. (2003) Supply chain coordination with contracts, in *The Handbook of Operation's Research and Management Science: Supply Chain Management* (Eds) S. Graves and T. de Kok, Kluwer, Amsterdam, The Netherlands, pp. 229–339.

Cachon, G. P. and Fisher, M. (2000) Supply chain inventory management and the value of shared information, *Management Science*, **46**, 1032–48.

Chao, J. C. and Phillips, P. (1999) Model selection in partially nonstationary vector autoregressive processes with reduced rank structure, *Journal of Econometrics*, **91**, 227–71.

Chickering, D. M. (2002) Optimal structure identification with greedy search, *Journal of Machine Teaming Research*, **3**, 507–54.

Chopra, S. and Meindl, P. (2001) *Supply Chain Management: Strategy Planning and Operation*, Prentice Hall, Upper Saddle River, NJ.

Clark, T. E. and McCracken, M. W. (2001) Tests of equal forecast accuracy and encompassing for nested models, *Journal of Econometrics*, **105**, 85–110.

Conner, J., Carstensen, P. C., McEowen, R. A., and Harl, N. E. (2004) The ban on packer ownership and feeding of livestock: legal and economic implications. Available at http://www.econ. iastate.edu/outreach/agriculture/reports/PackerOwnership.pdf (accessed 28 February 2008).

Corradi, V. and Swanson, N. R. (2002) A consistent test for nonlinear out of sample predictive accuracy, *Journal of Econometrics*, **110**, 353–81.

DeJong, D. N., Nankervis, J. C., Savin, N. E. and Whiteman, C. H. (1992) The power problem of unit root tests in time series with autoregressive errors, *Journal of Econometrics*, **53**, 323–43.

Demiralp, S. and Hoover, D. K. (2003) Searching for the causal structure of a vector autoregression, *Oxford Bulletin of Economics and Statistics*, **65**, 745–67.

Diebold, F. X. and Rudebusch, G. D. (1991) On the power of Dickey–Fuller tests against fractional alternatives, *Economics Letters*, **35**, 673–82.

Engle, R. F. and Granger, C. W. J. (1987) Cointegration and error correction: representation, estimation, and testing, *Econometrica*, **55**, 251–76.

Ferguson, M. and Ketzenberg, M. E. (2006) Information sharing to improve retail product freshness of perishables, *Production and Operation Management*, **15**, 57–73.

Fiala, P. (2005) Information sharing in supply chains, *The International Journal of Management Science*, **33**, 419–23.

Grain Inspection and Packers Stockyard Administration (GIPSA) (2008) Packers and stockyards: statistics report (2006 reporting year), GIPSA, USDA. Available at http://archive.gipsa.usda.gov/pubs/2006_stat_report.pdf (accessed 26 April 2010).

Granger, C. W. J. (1969) Investigating causal relations by econometric models and cross-spectral methods, *Econometrica*, **37**, 424–38.

Granger, C. W. J. (1980) Testing for causality: a personal viewpoint, *Journal of Economics Dynamics and Control*, **2**, 329–52.

Granger, C. W. J. (1988) Some recent development in a concept of causality, *Journal of Econometrics*, **39**, 199–211.

Harvey, D., Leybourne, S. and Newbold, P. (1997) Testing the equality of prediction mean square errors, *International Journal of Forecasting*, **13**, 253–63.

Hawkins, D. M. (1976) Point estimation of the parameters of a piecewise regression model, *Applied Statistics*, **25**, 51–7.

Hendry, D. F. and Massmann, M. (2007) Co-breaking: recent advances and a synopsis of the literature, *Journal of Business and Economic Statistics*, **25**, 33–51.

Hwarng, H. W. and Xie, N. (2008) Understanding supply chain dynamics: a chaos perspective, *European Journal of Operation Research*, **184**, 1163–78.

Jennrich, R. I. (1970) An asymptotic Chi-square test for the equality of two correlation matrices, *Journal of the American Statistical Association*, **65**, 904–12.

Juselius, K. (2006) *The Cointegrated VAK Model*, Oxford University Press, Oxford.

Kasman, A. and Ayhan, D. (2008) Foreign exchange reserves and exchange rates in Turkey: structural breaks, unit roots, and cointegration, *Economic Modeling*, **25**, 83–92.

Kwiatkowski, D. K., Phillips, P. C. B., Schmidt, P. and Shin, Y. (1992) Testing the null hypothesis of stationarity against the alternative of a unit root, *Journal of Econometrics*, **54**, 159–78.

Love, H. A. and Burton, D. M. (1999) A strategic rationale for captive supplies, *Journal of Agricultural and Resource Economics*, **24**, 1–18.

Masih, R. and Masih, A. M. M. (1996) Macroeconomic activity dynamics and Granger causality: new evidence from a small developing economy based on a vector-correlation modeling analysis, *Economic Modelling*, **13**, 407–26.

Masih, R. and Masih, A. M. M. (1998) A multivariate cointegrated modeling approach in testing temporal causality between energy consumption, real income and prices with an application to two Asian LDCs, *Applied Economics*, **30**, 1287–9.

Mathews, K. H., Hahn, W. F., Nelson, K. E., Duewer, L. A. and Gustafson, R. A. (1999) US beef industry: cattle cycles, price spreads, and packer concentration, Technical Bulletin No. 1874, Economic Research Service, USDA.

Mendelson, H. and Tunca, T. I. (2007) Strategic spot trading in supply chains, *Management Science*, **53**, 742–59.

Mundlak, Y. and Huang, H. (1996) International comparison of cattle cycles, *American Journal of Agricultural Economics*, **78**, 855–68.

Park, M., Jin, Y. H. and Bessler, D. A. (2008) The impacts of animal disease crises on the Korean meat market, *Agricultural Economics*, **39**, 183–95.

Pearl, J. (2000) *Causality: Models, Reasoning, and Inference*, Cambridge University Press, Cambridge.

Phillips, P. (1996) Econometric model determination, *Econometrica*, **64**, 763–812.

Phillips, P. and McFarland, J. (1997) Forward exchange market unbiasedness: the case of the Australian dollar since 1984, *Journal of International Money Finance*, **16**, 885–907.

Qu, Z. J. and Perron, P. (2007) Estimating and testing structural changes in multivariate regression, *Econometrica*, **75**, 459–502.

Sahin, F. and Robinson Jr, E. P. (2002) Flow coordination and information sharing in supply chains: review, implications, and directions for future research, *Decision Sciences*, **33**, 505–536.

Sahin, F. and Robinson Jr, E. P. (2005) Information sharing and coordination in make-to-order supply chains, *Journal of Operations Management*, **23**, 579–98.

Schroeder, T. C., Jones, R., Mintert, J. and Barkley, A. P. (1993) The impact of forward contracting on fed cattle transaction prices, *Review of Agricultural Economics*, **15**, 325–37.

Spirtes, P., Glymour, C. and Scheines, R. (2000) *Causality, Prediction, and Search*, MIT Press, Cambridge, MA.

Swanson, N. R. and Granger, C. W. J. (1997) Impulse response functions based on a causal approach to residual orthogonalization in vector autoregressions, *Journal of the American Statistical Association*, **92**, 357–67.

Tiao, G. C. (1999) The ET interview: Professor George C. Tiao, *Econometric Theory*, **15**, 389–424.

Wang, Z. and Bessler, D. A. (2005) A Monte Carlo study on the selection of cointegrating rank using information criteria, *Econometric Theory*, **21**, 593–620.

Ward, C. E., Koontz, S. R. and Schroeder, T. C. (1998) Impacts from captive supplies on fed cattle transaction prices, *Journal of Agricultural and Resource Economics*, **23**, 494–514.

Xia, T. and Sexton, R. J. (2004) The competitive implications of top-of-the-market and related contract-pricing clauses, *American Journal of Agricultural Economics*, **86**, 124–38.

Zhang, F. (2006) Competition, cooperation, and information sharing in a two-echelon assembly system, *Manufacturing and Service Operations Management*, **8**, 273–91.

Zivot, E. and Andrews, D. W. K. (1992) Further evidence on the Great Crash, the oil-price shock, and the unit-root hypothesis, *Journal of Business and Economic Statistics*, **10**, 251–70.