Price and Volatility Spillover between Livestock and Related Commodity Markets

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Introduction

Over the past decade, several important events have had major impacts on agricultural markets. For example, in December 2003 the first case of bovine spongiform encephalopathy (BSE) was reported in the US, causing major disruptions to livestock and meat markets. Similarly, the swine influenza (H1N1) outbreak that occurred in the US in 2009, also affected these markets. Some consumers reacted violently to these food safety alerts by immediately changing their buying patterns and reducing consumption of the affected products (Ding, Veeman and Adamowicz, 2010). For example, in the case of the BSE outbreak, importing countries closed their doors to products from the US, in some cases for several years (Mutondo, Brorsen and Henneberry, 2009). Furthermore, major market trends such as recent increases in global ethanol demand and production have also had substantial impact on livestock and related markets (Anderson, Anderson and Sawyer, 2008). Following passage of the Energy Policy Act of 2005, corn prices have increased markedly and this also has influenced livestock markets through increasing feed prices and price volatility. Such major market events can affect both price levels as well as price variation for relatively long periods of time. Therefore, the unprecedented high levels of price and price volatility fluctuations in recent years have elevated concerns about market spillovers. That is, how do changes affecting prices and price volatility spillover to markets of related commodities?

Policy makers need to understand market price and volatility spillovers as they design policies because often times the market effects are much broader than anticipated (e.g., the impact of ethanol production mandates on livestock markets). However, little research has documented how price and price volatility spillovers translate across markets. Scant empirical evidence is present regarding the magnitude of price and price volatility spillovers from one agricultural market to another. The objective of this study is to identify the mechanism of price and volatility transmissions by analyzing price and volatility spillovers across livestock and related commodity markets in recent years during times of major market events. The livestock commodities that are considered in this analysis are live cattle, feeder cattle and lean hogs. In addition, corn and soybeans are also included since price changes in these commodities affect livestock markets. The markets considered in this study are related because they share common information, are substitutes or complements in demand and compete in the usage of common inputs, such as feedstuffs.

Our study provides several important contributions. First, identifying how price and price variance relationships have changed over time is essential information to producers and traders in the livestock and grain sector. Having a keen understanding of the spillovers for example of corn markets to livestock is critical as producers make production, marketing, and risk management decisions. Second, our results have information policy makers need to understand as they design policies that may be intended to support an industry, such as the ethanol industry, without fully considering its impacts on corn price and price volatility as well as spillovers these have to other markets. In addition, our study illustrates the application of a method of solving the identification problem that arises in simultaneous equations models based on the heteroskedasticity of the structural shocks. The illustration of this method is useful since it has not been broadly used in the agricultural economics literature.

Previous Research

Spillover effects have been mostly explored in financial markets, particularly focusing on exchange rates, interest rates and bonds and in energy markets, predominantly among crude oil and gasoline (see Skintzi and Refenes, 2006; Aloui, 2007; Arouri, Jouini and Nguyen, 2011 and

Bubak, Kocenda and Zikes, 2011). However, only a few studies involve the analysis of price and/or volatility transmissions (also called spillovers) among agricultural markets. Buguk, Hudson and Hanson (2003) examined price volatility spillovers in US catfish markets. They estimated univariate exponential generalized autoregressive conditional heteroskedasticity (GARCH) models to test price volatility spillovers in the catfish supply chain. Significant unidirectional spillover existed from corn, soybean and menhaden prices to catfish feed, farm, and wholesale catfish prices. Following a similar methodology, Apergis and Rezitis (2003) and Rezitis (2003) investigated volatility spillover effects in Greek agricultural markets using a multivariate GARCH model. Significant positive volatility transmissions were present from agricultural input and retail food prices to agricultural output prices. Furthermore, retail meat markets (i.e., lamb, beef, pork and poultry) used information from the other meat markets when forming price expectations. In a more recent article, Wu, Guan, Myers (2010) proposed a trivariate volatility spillover model to compare three model specifications with different assumptions on the spillover effects from crude oil futures price to corn cash and futures prices. They specified three different models: a constant spillover model (containing constant spillover parameters), an event spillover model (including differing spillover parameters before and after the introduction of the Energy Policy Act of 2005) and a substitution spillover model (containing time-varying spillover parameters allowed to vary with the ratio of fuel ethanol consumption to gasoline consumption). The trivariate model was estimated using T-GARCH (threshold) and BEKK-GARCH (Baba–Engle–Kraft–Kroner) models to account for asymmetric volatility effects and utilized error correction models as a proxy of the mean equations for these GARCH processes. Volatility spillovers from crude oil prices to corn cash and futures prices were detected, in the case of the constant spillover model and an increase in the intensity of spillover effects since Energy Policy Act of 2005 in the case of the event spillover model. Despite the popularity of GARCH type models in assessing spillover effects in agricultural markets, a notable drawback of this type of model is the failure to account for cointegration relationships between price series (Serra, Zilberman and Gil 2011). Serra, Zilberman and Gil (2011) evaluated price and volatility transmissions in the Brazilian ethanol industry implementing an approach proposed by Seo (2007) where an error correction model and a multivariate GARCH process are jointly estimated in a single step. Ethanol price levels and volatility were positively related to crude oil and sugar prices, in both the short and long run.

Focusing on analyzing price transmissions between energy (i.e., crude oil and ethanol) and agricultural markets, Saghaian (2010) and Zhang et al. (2009) used VEC models (a simultaneous equations approach) to account for the presence of cointegrating relationships in prices. Saghaian (2010) analyzed causal relationships across five US price series: corn, soybeans, wheat, ethanol and crude oil obtaining mixed results. That is, directed acyclic graphs (DAGs) of the residuals of the VEC model indicated that there were no causal links between energy and agricultural markets. However, results of Granger causality tests indicated crude oil prices Granger cause corn, soybeans, and wheat prices. Zhang et al. (2009) investigated the causality of fuel prices on agricultural commodity prices. They estimated a VEC model with impulse response functions and error variance decomposition analyses utilizing ethanol, gasoline, oil, corn and soybean prices. No long-run relation existed among fuel (ethanol, oil and gasoline) prices and agricultural commodity (corn and soybean) prices, which is consistent with the DAGs assessment results obtained by Saghaian (2010). In addition, although short run relations between fuel and agricultural commodity prices were present they were not persistent.

Kim and Doucouliagos (2008) employed realized volatility and covariation methods to estimate a vector autoregression (VAR) model utilizing realized volatility and correlation estimates (instead of prices) for corn, soybean and wheat futures prices. The authors argued that this method is less restrictive than GARCH models and does not depend on the underlying model assumptions. Volatility spillover effects were evaluated through generalized impulse responses. The three estimated volatilities were closely related over time based on the existence of volatility spillover effects from one commodity to the others.

Finally, Du, Yu and Hayes (2011) used a Bayesian analysis to investigate volatility spillover effects from crude oil to agricultural commodity markets (i.e., corn and wheat). Two types of models were estimated, a univariate stochastic volatility model with Merton jump and bivariate stochastic volatility models. They confirmed the existence of volatility transmissions and concluded that factors such as scalping, speculation, and petroleum inventories help to explain crude oil price volatility.

Methodology

This study uses a structural vector autoregression model (SVAR) to assess price and price volatility spillovers effects between livestock (feeder cattle, live cattle and lean hogs) and related feed grain (corn and soybeans) markets. Particularly, impulse response functions (IRFs) are obtained to evaluate the time path of reactions among the included price series. In addition, a forecast error variance decomposition (FEVD) analysis is conducted to determine how much of the forecast error variance for any variable in the system, is explained by innovations to the other variables. Finding evidence about a particular variable being affected by one or more variables enables us to determine whether volatility spillover effects exist between corresponding markets.

Of particular interest in this study is to illustrate an alternative approach to identify the contemporaneous relationships in VAR models. This is important because analysis using IRFs is sensitive to the ordering of the variables in the system and imposing recursiveness identification or economic assumptions cannot be justified (implicitly establishes the direction of causation). Therefore, we implement the method of identification through heteroskedasticity proposed by Rigobon (2003).

Identification through Heteroskedasticity

There are several different approaches used in the VAR literature to identify contemporaneous relationships between variables. The most common approach is Cholesky decomposition, which imposes a recursive causal structure from the earliest variables to the latest variables but not the other way around. However, this approach is known to be overly restrictive and results are sensitive to the ordering of data series included in the VAR. To overcome this problem several studies in the agricultural economics literature have implemented the method of Directed Acyclic Graphs (DAGs) proposed by Bessler and Akleman (1998) to achieve identification in VAR models (see Awokuse and Bessler; 2003; Babula, Bessler and Payne, 2004 and Wang and Bessler, 2006). This method assigns causal flows between variables based on partial correlations. However, causal flow can be sensitive to the level of significance chosen by the researcher. For example, Awokuse and Bessler (2003) considered various levels of significance in order to achieve an unambiguous causal structure of the variables in contemporaneous time. After trying several different levels of significance, they found an unambiguous causal ordering at the 30% significance level. In addition, another drawback of this method is that within small sample sizes, there is a considerable probability of omitting an edge in the model (Spirtes, Glymour, and Scheines, 1993).

We follow the approach proposed by Rigobon (2003) where the identification problem is solved based on the heteroskedasticity of structural shocks. In this method, identification is achieved by exploiting the change (if any) in the variance of structural shocks implicit in the data. In other words, it is possible to specify the model by recognizing periods (regimes) of high volatility from periods of low volatility. An advantage of this approach is that it does not rely on a specific ordering of variables in the VAR. This method estimates, rather than imposes, the pattern of contemporaneous correlations between structural shocks. Since this method relies on the identification of regimes, major market events such as the BSE outbreak, H1N1 outbreak, or Energy Policy Act of 2005 provide information to help identify causes of regimes in our data, as we test for structural shocks.

S*tructural VAR*

We estimate two SVAR models: one focused on price and the other on volatility spillover effects. SVAR models are considered in order to impose the identification restrictions based on the contemporaneous causality of the system variables. Using R, the estimation of the SVAR is conducted in two steps. First, a reduced form VAR is estimated and then, the identification restrictions, which in this study are obtained from implementing the approach of identification through heteroskedasticity, are imposed into the reduced form VAR innovations matrix. Once the identification restrictions are entered into this matrix, the SVAR can be estimated. The reduced form VAR model takes the form:

$$C_t = a_{10} + \sum_{i=1}^{p} a_{11}(i)\, C_{t-i} + \sum_{i=1}^{p} a_{12}(i)\, LC_{t-i} + \sum_{i=1}^{p} a_{13}(i)\, LH_{t-i} + \sum_{i=1}^{p} a_{14}(i)\, FC_{t-i} + \sum_{i=1}^{p} a_{15}(i)\, S_{t-i} + \varepsilon_{Ct}$$

$$LC_t = a_{20} + \sum_{i=1}^{p} a_{21}(i)\, C_{t-i} + \sum_{i=1}^{p} a_{22}(i)\, LC_{t-i} + \sum_{i=1}^{p} a_{23}(i)\, LH_{t-i} + \sum_{i=1}^{p} a_{24}(i)\, FC_{t-\mathrm{i}} + \sum_{i=1}^{p} a_{25}(i)\, S_{t-i} + \varepsilon_{LCt}$$

$$LH_t = a_{30} + \sum_{i=1}^{p} a_{31}(i)\, C_{t-i} + \sum_{i=1}^{p} a_{32}(i)\, LC_{t-i} + \sum_{i=1}^{p} a_{33}(i)\, LH_{t-i} + \sum_{i=1}^{p} a_{34}(i)\, FC_{t-i} + \sum_{i=1}^{p} a_{35}(i)\, S_{t-i} + \varepsilon_{LHt}$$

$$FC_t = a_{40} + \sum_{i=1}^{p} a_{41}(i)\, C_{t-i} + \sum_{i=1}^{p} a_{42}(i)\, LC_{t-i} + \sum_{i=1}^{p} a_{43}(i)\, LH_{t-i} + \sum_{i=1}^{p} a_{44}(i)\, FC_{t-i} + \sum_{i=1}^{p} a_{45}(i)\, S_{t-i} + \varepsilon_{FCt}$$

$$S_t = a_{50} + \sum_{i=1}^{p} a_{51}(i)\, C_{t-i} + \sum_{i=1}^{p} a_{52}(i)\, LC_{t-i} + \sum_{i=1}^{p} a_{53}(i)\, LH_{t-i} + \sum_{i=1}^{p} a_{54}(i)\, FC_{t-i} + \sum_{i=1}^{p} a_{55}(i)\, S_{t-i} + \varepsilon_{St}$$

where, *LC*, *FC*, *LH*, *C* and *S* correspond to either price or volatility for live cattle, feeder cattle, lean hogs, corn and soybean futures, respectively.

We first conduct standard time series tests in order to evaluate the properties of each price and volatility data series. We test for the presence of unit roots and subsequently, for cointegration. If we find a cointegration relationship between two or more variables, structural vector error correction (SVEC) models are estimated instead of SVAR models. Next, we perform a Granger causality test and finally, after estimating the SVAR (or SVEC) models, we analyze the IRFs and FEVDs.

Results

Weekly average prices and historical volatilities derived from nearby futures contracts are utilized to evaluate spillover effects in livestock and related commodity markets. The data used in this study, correspond to the period from January 1995 to April 2012 in the case of price variables and from January 1995 to October 2010 in the case of historical volatility variables, totaling 904 and 826 observations per commodity, respectively. These data were obtained from the CRB (Commodity Research Bureau) database. We use nearby futures contracts to determine prices and historical volatilities up until fifteen days prior to expiration, at which point we rollover to the next contract. Figures 1 and 2 present price and historical volatility plots for each commodity, respectively. Comparing the plots of price variables versus historical volatility variables, it is noticeable that prices appear less stationary. To test for the presence of a unit root, an Augmented Dickey-Fuller (ADF) test was conducted on each data series. Table 1 presents the results of this test.

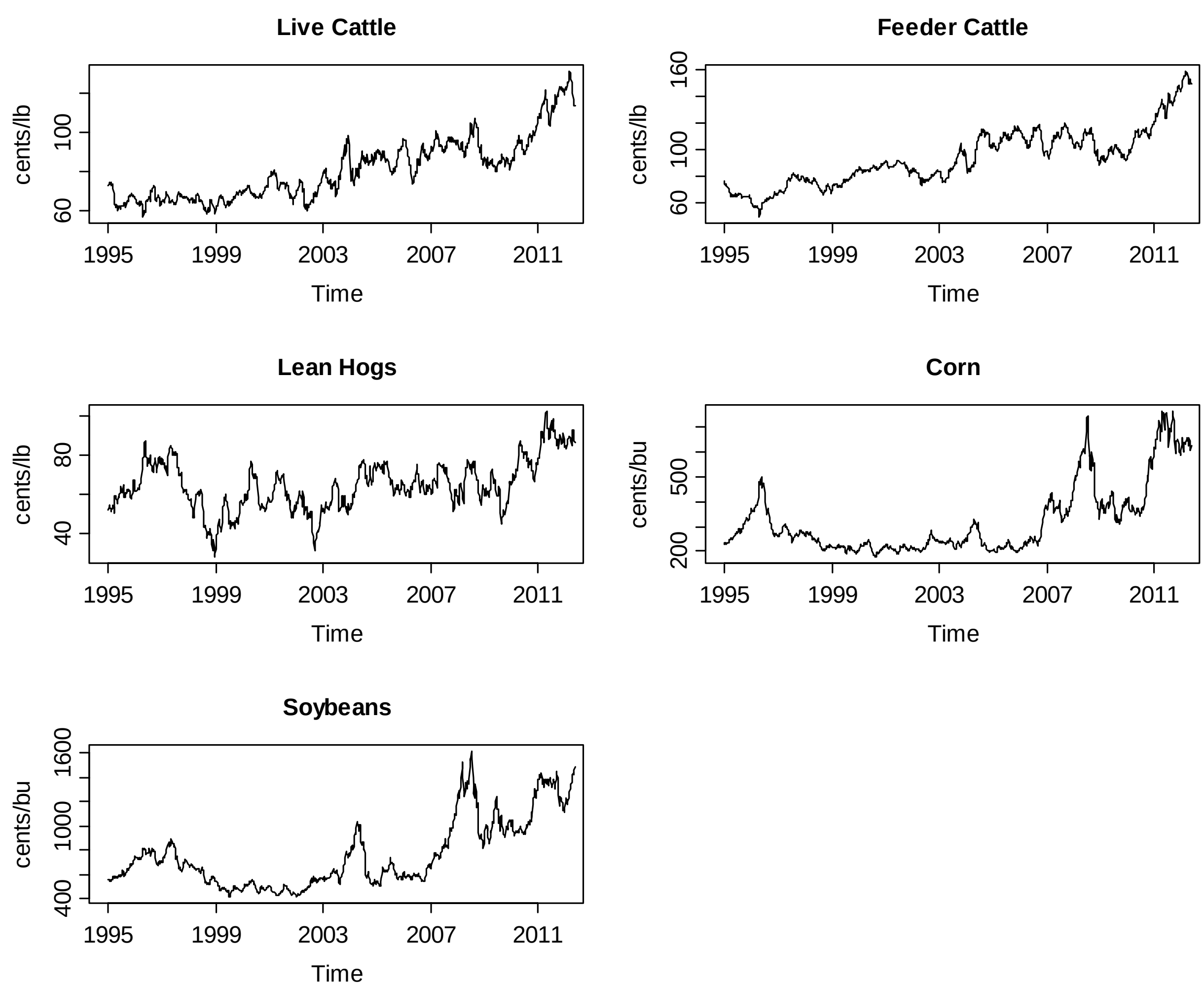

Figure 1. Livestock and related agricultural commodity prices

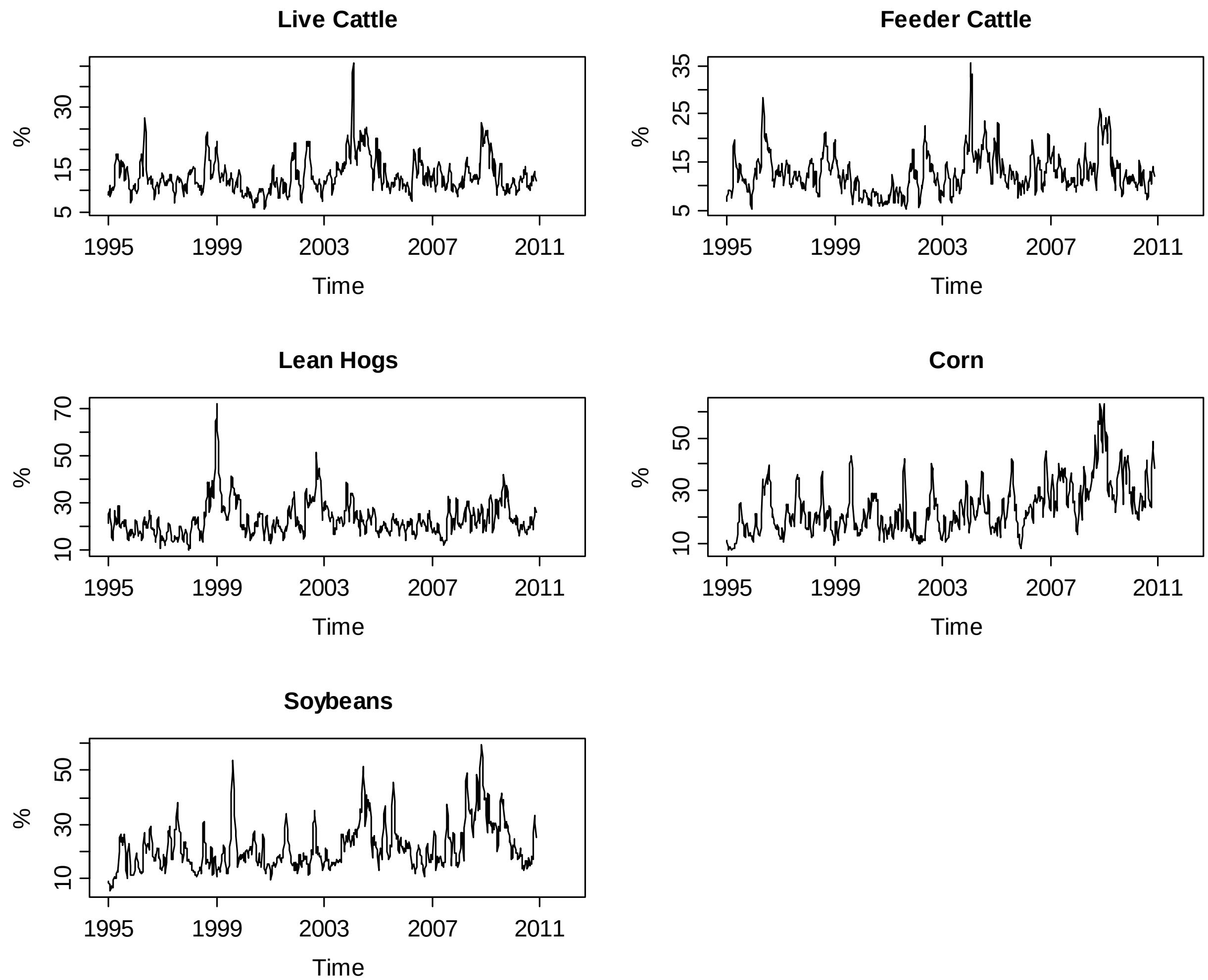

Figure 2. Livestock and related agricultural commodity historical volatilities

Table 1. Augmented Dickey-Fuller Test Results

Variable	**Price Variable t-statistic**	**Volatility Variable t-statistic**
Live Cattle	-4.2601*	-7.5782*
Feeder Cattle	-2.6954	-8.0878*
Lean Hogs	-3.6165*	-6.9973*
Corn	-2.1042	-8.2332*
Soybeans	-2.0221	-7.4372*

Note: * indicates the rejection of the null hypothesis of a unit root at the 0.05 level. The critical value at this level is -3.41. AIC was used to determine appropriate lag lengths.

The ADF test corresponds to the case when the intercept and trend are present in the regression and the lag length was set to be selected using the AIC. Regarding price series, the ADF test indicates that all variables except *LC* and *LH* are non-stationary. Thus, we need to difference these data and conduct cointegration tests. On the other hand, results indicate that all historical volatility series are stationary. Thus, there is no need to apply any transformation in these data and no cointegration tests need to be conducted.

The Johansen cointegration test, which tests the null hypothesis of no cointegration versus the alternative of at least one cointegrating term, was conducted using the three non-stationary price variables. Results indicate that one out of four variable combinations evaluated is cointegrated (table 2). An SVEC model is therefore chosen to evaluate price spillover effects between livestock and related feed grain markets.

Table 2. Johansen Cointegration Test Results

Null Hypothesis	**Test Statistic** (λ_{max})
Feeder Cattle, Corn and *Soybeans*	
$r = 0$	13.83
$r \leq 1$	8.22
$r \leq 2$	2.40
Feeder Cattle and *Corn*	
$r = 0$	8.75
$r \leq 1$	2.25
Feeder Cattle and *Soybeans*	
$r = 0$	8.15
$r \leq 1$	2.28
Corn and *Soybeans*	
$r = 0$	13.85*
$r \leq 1$	1.56

Notes: * denotes rejection of the null hypothesis at the 10% significance level. The critical values at the 10% significance level under the first null hypothesis are: 19.77, 13.75 and 7.52, respectively, whereas the critical values at the same significance level under the other three hypotheses are 13.75 and 7.52, respectively. The cointegrating term included a constant term, but not a trend.

Before proceeding to estimate the SVEC and SVAR models, bivariate Granger Causality tests are conducted to evaluate if a particular variable have predictive power on other variables. Finding evidence that some variables Granger cause others corroborates the use of a multivariate model and in addition, determines the extent to which lagged price or volatility variables for one market influence variables in another market. Table 3 shows the results of this test.

Table 3. Bivariate Granger Causality Test Results

Null Hypothesis	**Price Variable p-value**	**Volatility Variable p-value**
Live Cattle		
LC does not Granger cause *C*	0.2330	0.5063
LC does not Granger cause *LH*	0.0036***	0.0078***
LC does not Granger cause *FC*	0.0172**	0.1884
LC does not Granger cause *S*	0.5112	0.2692
Feeder Cattle		
FC does not Granger cause *C*	0.6558	0.9003
FC does not Granger cause *LC*	0.0368**	0.0001***
FC does not Granger cause *LH*	0.6328	0.9500
FC does not Granger cause *S*	0.6872	0.4262
Lean Hogs		
LH does not Granger cause *C*	0.1057	0.3514
LH does not Granger cause *LC*	0.6485	0.0155**
LH does not Granger cause *FC*	0.0845*	0.2096
LH does not Granger cause *S*	0.0694*	0.7183
Corn		
C does not Granger cause *LC*	0.0890*	0.3406
C does not Granger cause *FC*	0.0658*	0.7085
C does not Granger cause *LH*	0.3072	0.1024
C does not Granger cause *S*	0.0023***	0.5710
Soybeans		
S does not Granger cause *C*	0.4226	0.2908
S does not Granger cause *LC*	0.9266	0.4766
S does not Granger cause *LH*	0.8323	0.5059
S does not Granger cause *FC*	0.1743	0.5477

Notes: ***, ** and * indicate that the null hypothesis has been rejected at the 1%, 5% and 10% significance level, respectively. AIC was used to determine appropriate lag lengths.

The bivariate Granger causality tests indicate that *LC* Granger causes *LH* and *FC* prices, but only *LH* volatilities. As expected, *FC* Granger causes both *LC* prices and volatilities. In the case of *LH*, we observe a Granger causal relationship with *FC* and *S* prices and *LC* volatilities. An interesting finding is that *C* does Granger cause *LC*, *FC* and *S* prices, but does not cause any volatility variable. A curious finding is that *S* does not Granger cause any of the variables present in the system. These findings suggest that the use of multivariate models is adequate and in addition, provide us with some intuition about causal relationships across price and volatility variables.

Next, we estimate a SVEC model using price data (which incorporates the cointegrating term found between corn and soybeans prices) and a SVAR model using volatility data. Here, the identification approach proposed by Rigobon (2003) is implemented. After estimating these models, IRFs and FEVDs are calculated and analyzed. These assessments will reveal whether price and/or volatility spillovers exist between livestock and related feed grain markets.

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