Basis Volatilities of Corn and Soybean in Spatially Separated Markets: The Effect of Ethanol Demand

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Selected Paper prepared for presentation at the Agricultural and Applied Economics Association's 2009 AAEA & ACCI Joint Annual Meeting, Milwaukee, WI, July 26-28, 2009.

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Abstract

The 2006 spike in corn-based ethanol demand has contributed to the increase in basis volatility in corn and soybean markets across the United States, which has, to a significant degree, led to the observed large jumps in the prices of the two commodities. Despite the overall rise in basis volatility, there remain differences in the degree of volatility that exists across spatially separated markets, which might be caused by factors such as transportation costs, seasonality, and time-to-delivery. The focus of this study is threefold first, this work models basis data for six corn and soybean markets by using a multivariate GARCH model that incorporates the spatial linkages of these markets; next, the model is used to investigate whether the increase in ethanol demand has significantly aided in the rise of basis volatilities; and last, the spatio-temporal linkages among basis volatilities in different markets are examined under various scenarios of spot-price shocks.

KEYWORDS: basis, spatially separated markets, multivariate GARCH, volatility

JEL classification codes: Q11, Q14, G13

* The authors would like to acknowledge and thank Kevin McNew at Cash Grain Bids Inc. for allowing the use of the cash price data in this research. Direct correspondence to Anton

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Basis is an important concept in agricultural marketing, because it is a useful tool for hedging risk for both buyers and sellers of commodities. This is primarily because of the significantly decreased amount of variability that basis exhibits relative to that observed in the futures prices of a commodity. Since basis is the difference between the local cash price and the futures price for a particular commodity, risk hedgers can take advantage of the reduced variability that is associated with these differences.[1] This smaller variability implies a significant decrease in risk that a buyer or seller faces when purchasing futures contracts. Accordingly, a change in market conditions that would increase the variability of basis would decrease the ability to hedge price risk.

In August 2005, the U.S. government passed the Energy Policy Act of 2005, which increased the number of tax incentives and loan guarantees for producers of alternative energy sources, as well as increased the required amount of biofuel (mainly ethanol) that must be mixed with gasoline within the United States. Accordingly, this bill has led to a significant increase in the demand for ethanol-based fuel production, and accordingly for corn. This has raised the price of corn and the acreage that was dedicated to growing the crop (United States Department

[1] Specifically, hedgers will choose to take two opposite positions: one in the cash market and another in the futures market.

of Agriculture (USDA-NASS)). Consequentially, this has reduced the planting and production of soybeans, which is a crop that can be planted on the same land as corn. In effect, the reduction of the supply of soybeans has, too, significantly raised the price of this commodity. As shown in Figure 1 and Figure 2, the changes in futures prices were rapid and with significant variability. This implies that unless spot prices at local markets are perfectly correlated with futures prices, there is an increase in the probability that the basis for the individual markets may have become more volatile as well.

Another important aspect of basis volatility analysis is the transmission of changes in basis across linked markets. In the United States, some markets are net exporters of corn and soybeans, while some are net importers. For example, a market in Iowa is a large producer of corn and soybeans, and Texas, where the livestock industry is prominent, is a large consumer of these crops. We might, then, assume that these markets are linked by the transport of corn and soybeans. Accounting for these spatial linkages can be important for developing a specification that appropriately models basis volatility in economically connected markets.

Although there has been research that attempts to explain factors affecting basis and forecast future basis, none attempts to directly model basis volatility. Using a multivariate generalized autoregressive conditionally heteroskedastic (GARCH) specification, this study seeks to appropriately model the volatility structure of basis in spatially separated U.S. markets. After this model is identified, it is used to determine the effects of the increase in the demand for ethanol on the basis volatility of corn and soybeans. Prediction analysis motivates a discussion of potential policy implications that may significantly influence the corn and soybean markets. The remaining sections are as follows: a survey of literature on volatility analysis in agricultural markets is presented; next, we show a specification of a multivariate GARCH (MGARCH) model; lastly, a brief outline of the data and preliminary graphical analyses are discussed. Future work includes an application of the MGARCH specification to basis data in spatially separated U.S. markets, an associated implementation for forecast analysis, and a discussion of policy implications.

Literature on Volatility in Agricultural Markets

Although basis is an important topic in the field of agricultural marketing and market strategy (Tomek 1997; Hauser, Garcia, and Tumblin 1990), there has been significantly less research in this area relative to the analysis of futures prices of agricultural commodities. Mainly, this might be due to the much lesser availability of local cash price data, which are necessary for the determination of basis time series. However, there are a number of studies that attempt to explain factors that are significant in affecting basis (for example, see Davis and Hill 1974; Garcia and Good 1983; Kahl and Curtis 1986; Tilley and Campbell 1996, and Naik and Leuthold 1991). In general, these find significant effects of grain storage capacity, competition, and transportation costs as factor influencing basis.

Additionally, there have been studies that examine methods for forecasting basis. Hauser, Garcia, and Tumblin (1990) find that simple forecasting methods that use historical averages of basis are better at predicting soybean basis than more sophisticated specifications. Dhuyvetter and Kastens (1998) compared practical methods of basis forecasting for wheat, corn, milo, and soybeans in Kansas, and found that the optimal choice of years necessary to forecast basis differed by crop. Taylor, Dhuyvetter, and Kastens (2006) examined the benefits of including current market information (basis deviation from historical averages), finding that simple forecast models that include current market information improve post-harvest basis forecasts for wheat, soybeans, corn, and grain sorghum in Kansas markets. Finally, Jiang and Hayenga (1997) study basis patterns in corn and soybean markets across the United States and determine that using an ARIMA model that incorporates seasonal patterns improves the accuracy of basis forecasting.

However extensive the research of basis forecasting, there are no studies that attempt to directly model the volatility of agricultural basis. Nonetheless, there has been a significant amount of literature devoted to volatility analysis of futures prices in agricultural commodities. We can look to this literature to examine the factors that might be relevant in modeling basis volatility, because there is a close relationship between basis and futures prices.

There are several aspects that have been found significant in affecting the variability of agricultural commodity prices. Anderson (1985) that a main factor that influences price volatilities in grain markets is seasonality. The importance of seasonality as well as lagged volatility was also found by Kenyon et al. (1987). Others that find the statistical significance of seasonality effects on futures price volatility include Hennessy and Wahl (1996) and Yang and Brorsen (1993) for corn, soybeans, and wheat, Goodwin and Schnepf (2000) for corn and wheat, and

Chatrath et al. (2002) for soybeans, corn, wheat, and cotton. Also, evidence that lagged volatility is important was supported by Streeter and Tomek (1992) and Chatrath et al. (2002).

Additionally, there has been research that models agricultural commodity futures prices using various GARCH specifications. Manfredo, Leuthold, and Irwin (2001) provide an evaluation of several methods for estimating future cash price volatility for fed cattle, feeder cattle, and corn cash price returns using a GARCH model, implied volatility from options, and integrated specifications. They find that the integrated specifications provide the best forecasts when both the time series and implied volatility data are available. Similarly, Ramirez and Fadiga (2003) propose an asymmetric-error GARCH model and compare its forecasting performance to the normal-error and Student-t GARCH specifications. The study finds that when the error term is asymmetrically distributed, their model provides improved forecasts for soybean, sorghum, and wheat futures prices.

Finally, there are two studies that provide analyses closest to the one that is proposed for this study. Crain and Lee (1996) study the effects of thirteen various farm programs on wheat spot and futures price volatilities between 1950 – 1993. They find that, in general, the mandatory farm programs have lowered the volatility of wheat prices, while voluntary farm programs have increased volatility. However, Yang, Haigh, and Leatham (2001) apply several GARCH model specifications to corn, soybeans, wheat, oats, and cotton futures prices in order to measure whether there was an increase in price volatility following the agricultural liberalization policies in the FAIR Act (1996). Unlike Crain and Lee (1996), their results indicate that there was an increase in the volatility of corn, soybeans, and wheat prices, insignificant change in the price volatility of oats, and a decrease in the volatility of cotton.

Specification of the M-GARCH Model

An assumption with standard time series modeling is a constant variance. However, in financial data, including that in agricultural markets, this assumption might not be realistic. For example, it is often observed that periods of high market volatility are typically clustered together, indicating a strong dependence between market factors and past variability shocks. The first model to deal with heteroskedastic error variances was proposed by Engle (1982), spawning a large literature on variations of the original autoregressive conditional heteroskedasticity (ARCH) specification.[2] An extension of the ARCH model is the generalized autoregressive conditional heteroskedasticity specification (GARCH), which was proposed by Bollerslev (1986). GARCH considers that the conditional variance of the error process is related to both the squares of the past errors as well as the lagged conditional variances. A standard, univariate GARCH(1,1) model is as follows:

$$y_t = \sigma_t \varepsilon_t$$

$$\sigma_t^2 = \alpha_o + \alpha_1 y_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{1}$$

[2]See Bollerslev, Chou, and Kroner (1992) for a survey of these models.

where $\varepsilon_t \sim N(0,1)$. Additionally, there has been an exhaustive literature that has examined variations of the univariate GARCH specification (see Bollerslev, Chou, and Kroner (1992) for a survey of GARCH models and their applications). However, for the analysis at hand, it is necessary to consider a model that can simultaneously analyze the relationship of volatilities in multiple markets. In this case, a multivariate GARCH (MGARCH) model is appropriate.

Since the objective of this study is to examine basis volatility in spatially linked markets, the MGARCH specification is a tool that is capable of explaining the relationship between volatilities and co-volatilities in several markets. Using the MGARCH model, it is possible to provide an appropriate analysis of posed questions. For example, whether a shock to the volatility of the basis in a supplier market lead an increase in basis variability in a another supplier market or a demand market, as well as the speed at which these shocks might be transmitted. Similarly, it possible to determine whether there is a direct (through the conditional variance) transmission of a variability shock to another market, or if the transmission occurs through the conditional covariances. Also, we can consider the effects of a potential structural change, such as an increased demand for ethanol, on basis volatility in the short- and long-run.

To define a specification of a multivariate GARCH model that can be used for this analysis, we use the notation in Bauwens, Laurent, and Rombouts (2006). Consider a stochastic process y_t of dimension $N \times 1$, which is conditioned on a set of past information up to time $t-1$, denoted as I_{t-1}. The process can be modeled as follows:

$$y_t = \mu_t(\theta) + \varepsilon_t$$

$$\varepsilon_t = H_t^{1/2}(\theta) \cdot z_t \tag{2}$$

where $\mu_t(\theta)$ is the vector of the conditional mean, $H_t^{1/2}$ is an $N \times N$ positive definite matrix, and the random error term, z_t, is assumed to have a mean vector 0_N and a variance structure that is an identity matrix of order N. Additionally, $H_t^{1/2}$ is the Cholesky decomposition of H_t, which is the conditional variance matrix of y_t and can be expressed as follows:

$$\begin{aligned} \mathrm{Var}(y_t|I_{t-1}) \quad = \quad \mathrm{Var}_{t-1}(y_t) &= \mathrm{Var}_{t-1}(\varepsilon_t) \\ &= H_t^{1/2}\mathrm{Var}_{t-1}(z_t)(H_t^{1/2})' \\ &= H_t \end{aligned}$$

The structure of the model as a whole, then, is determined by the specification of H_t. Bauwens, Laurent, and Rombouts (2006) provides a comprehensive overview of a number of different approaches for defining H_t. For this study, we consider using the class of conditional correlation models, which are nonlinear combinations of univariate GARCH models. In these models, it is possible to separately specify the individual conditional variances and the conditional correlation matrix between individual series. Additionally, these models do not require the estimation of as many parameters as alternative specification, and so, might be subject to easier estimation methods. Specifically, we consider using a dynamic conditional correlation (DCC) model, which allow for the conditional correlation matrix to be time-dependent.[3] Following Engle (2002), the $DCC(1,1)$ model for H_t is as follows:

$$H_t = D_t R_t D_t \tag{3}$$

where

$$D_t = diag(h_{11t}^{1/2} \cdot h_{22t}^{1/2} \cdots h_{NNt}^{1/2}) \tag{4}$$

In each univariate GARCH specification, h_{iit}, we specify a dummy variable that captures the effect of an increased demand for ethanol after the year 2006. Also, due to the significant effects of seasonality on basis, it might be necessary to consider the inclusion of a function, $s(t)$, that appropriately models these effects. This is as follows:

$$h_{iit} = \omega_i + \phi_i(ETH_{06}) + \psi_i s(t) + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{ii,t-1} \tag{5}$$

$$\text{for} \quad i = 1, \ldots, N$$

[3]This is in contrast to another type of conditional correlation models, which assume a constant correlation matrix. See Bollerslev (1990) for a description of the constant conditional correlation (CCC) models.

Additionally, the term R_t is defined as:

$$R_t = diag(q_{11,t}^{-1/2} \cdots q_{NN,t}^{-1/2}) \cdot Q_t \cdot diag(q_{11,t}^{-1/2} \cdots q_{NN,t}^{-1/2}) \tag{6}$$

such that Q_t is an $N \times N$ symmetric positive definite matrix as follows:

$$Q_t = (1 - \alpha - \beta)\overline{Q} + \alpha u_{t-1} u_{t-1}^{'} + \beta Q_{t-1} \tag{7}$$

where $u_{it} = \varepsilon_{it}/\sqrt{h_{iit}}$, $\overline{Q}$ is an $N \times N$ unconditional matrix of u_t, and

$$\alpha > 0$$
$$\beta > 0$$
$$\alpha + \beta < 1$$

Estimation of the parameters can be performed using maximum likelihood estimation. The log-likelihood function can be defined as follows:

$$LL_T(\theta) = -\frac{1}{2}\sum_{t=1}^{T} \log |H_t| - \frac{1}{2}\sum_{t=1}^{T} (y_t - \mu_t)^{'} H_t^{-1} (y_t - \mu_t) \tag{8}$$

According to Engle and Sheppard (2001), consistent estimation of the DCC model can be performed by using a two-step approach. First, it is necessary to estimate the parameters θ_1^*, which is the mean and volatility, and then the parameters θ_2^* that correspond to the correlation. In each step, the estimation yields consistent, though inefficient parameter values. However, using the set of estimated parameters $(\hat{\theta}_1^*, \hat{\theta}_2^*)$ as starting values in equation (8) will result in an asymptotically efficient estimator of the parameter set, θ. The quasi log-likelihood functions that need to be estimated to obtain the parameter set $(\hat{\theta}_1^*, \hat{\theta}_2^*)$ are as follows:

$$QLL1_T(\theta_1^*) = -\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{N}\left\{\log(h_{iit}) + \frac{(y_{it}-\mu_{it})^2}{h_{iit}}\right\} \tag{9}$$

$$QLL2_T(\theta_2^*) = -\frac{1}{2}\sum_{t=1}^{T}\left\{\log|R_t| + [D_t^{-1}(y_t-\mu_t)]' \cdot R_t^{-1} \cdot [D_t^{-1}(y_t-\mu_t)]\right\} \tag{10}$$

We can then use the estimate $\hat{\theta}$ to retrieve $\mu(\hat{\theta})$ and $H(\hat{\theta})$. All estimations are performed using the SAS software system.

U.S. Corn Markets and Soybean Markets

Data

Basis data in this research are calculated using spot prices from several major U.S. markets and nearby futures from the Chicago Board of Trade (CBOT). For corn, we use weekly spot price data for the following: Aberdeen, South Dakota; Alton, Iowa; Gulf, Louisiana; Muleshoe, Texas; Guntersville, Alabama; Candor, North Carolina; and, Western, Illinois. Soybean markets were: Aberdeen, South Dakota; Alton, Iowa; Gulf, Louisiana; Muleshoe, Texas; Raleigh, North Carolina; and, Western, Illinois.[4] For both commodities, Western, Illinois is selected as the central market, due to its proximity to a large port that is used to transport commodities from major supply markets to demand markets. The data spans the range between June 17, 1999 and January 10, 2008. Weeks during which there

[4]This data are supplied by Cash Grain Bids Inc. (www.cashgrainbids.com)

were missing observations were interpolated using an exponential spline method.

Summary statistics for the basis data are shown in Table 1 and for the basis difference pairs in Table 2. The time series of corn basis is shown in Figure 3 and for soybeans in Figure 4. Additionally, the time series of basis pairs between the central location and another market are shown in Figure 5 and Figure 6 for corn and soybeans, respectively. Finally, the sample annualized volatility for the corn and soybean basis are presented in Figure 7 and Figure 8. These indicate a significant increase in basis volatility in some of the markets after 2006.

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Table 1: Summary Statistics: Basis for Selected U.S. Markets

Market Location	**Obs.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Corn					
Aberdeen, South Dakota	445	-0.41641	0.15828	-0.78188	0.001
Alton, Iowa	445	-0.31607	0.12214	-0.85036	-0.01355
Western, Illinois	445	-0.25811	0.09492	-0.73444	-0.0035
Gulf, Louisiana	445	0.29317	0.13797	0.01063	0.679
Muleshoe, Texas	445	0.07825	0.19821	-1.24181	0.48421
Guntersville, Alabama	445	0.01872	0.18633	-0.99	0.355
Candor, North Carolina	445	0.16208	0.14576	-0.151	0.503
Soybeans					
Aberdeen, South Dakota	447	-0.61563	0.29541	-1.59333	0.8525
Alton, Iowa	447	-0.41733	0.33386	-2.02501	1.26
Western, Illinois	447	-0.28807	0.2704	-2.33697	1.3625
Gulf, Louisiana	447	0.34431	0.15852	-0.1915	1.445
Muleshoe, Texas	447	-0.90097	0.26989	-2.64833	-0.014
Raleigh, North Carolina	447	0.07856	0.15715	-0.242	1.1675

Table 2: Summary Statistics: Basis Pairs for Selected U.S. Markets

Market Location	**Obs.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Corn					
South Dakota-Illinois	445	-0.1583	0.13436	-0.45	0.45444
Iowa-Illinois	445	-0.05796	0.1075	-0.54886	0.50444
Louisiana-Illinois	445	0.55128	0.15499	0.258	1.038
Texas-Illinois	445	0.33636	0.18473	-0.90381	0.755
Alabama-Illinois	445	0.27683	0.17364	-0.67333	0.69
North Carolina-Illinois	445	0.42019	0.12991	0.07	0.83444
Soybeans					
South Dakota-Illinois	447	-0.32756	0.22169	-1.2725	0.84363
Iowa-Illinois	447	-0.12926	0.27795	-1.72336	1.15697
Louisiana-Illinois	447	0.63238	0.2312	-0.289	2.2703
Texas-Illinois	447	-0.6129	0.25351	-2.64156	-0.0175
North Carolina-Illinois	447	0.36663	0.23816	-0.379	2.2103

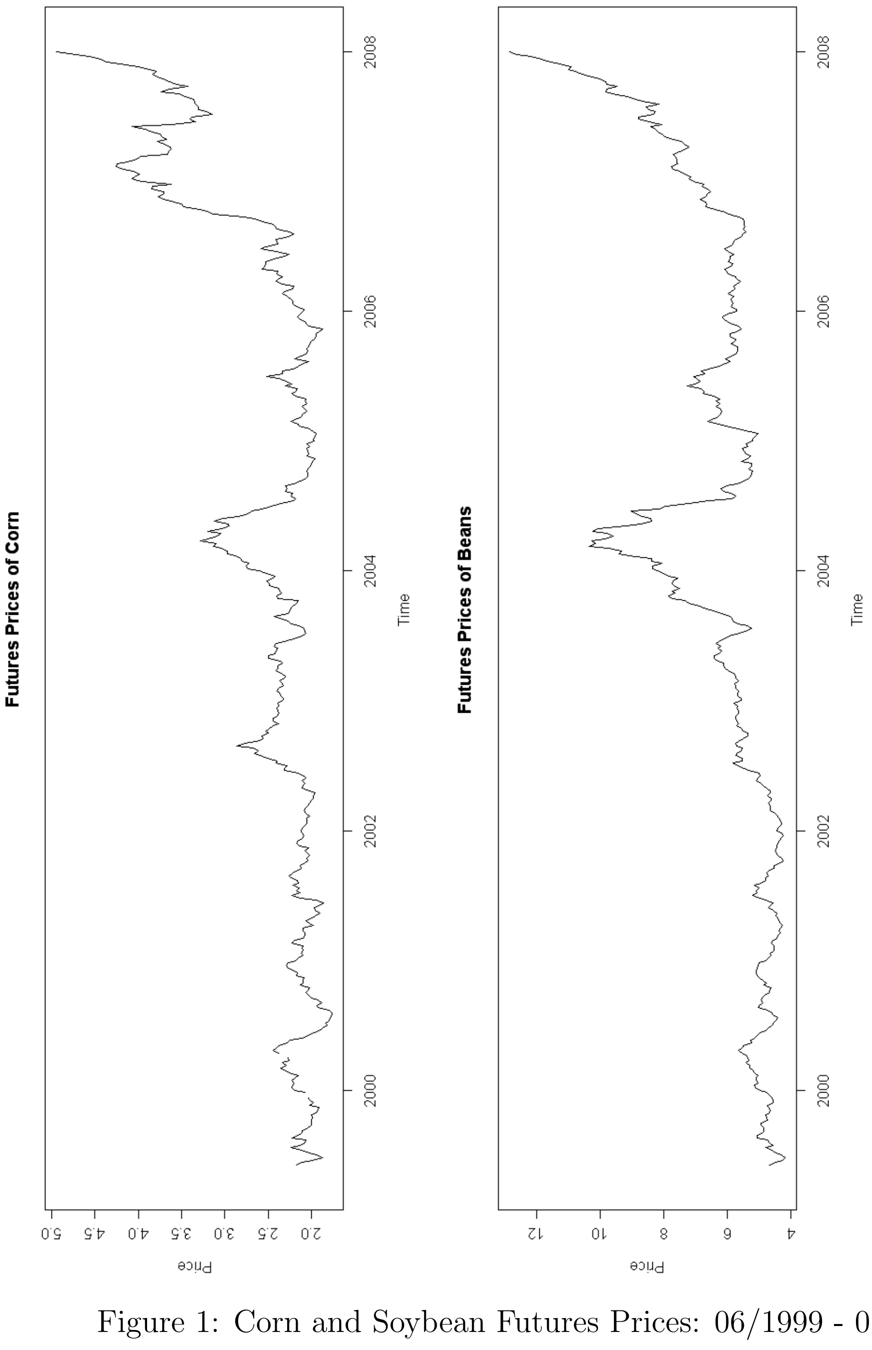

Figure 1: Corn and Soybean Futures Prices: 06/1999 - 01/2008

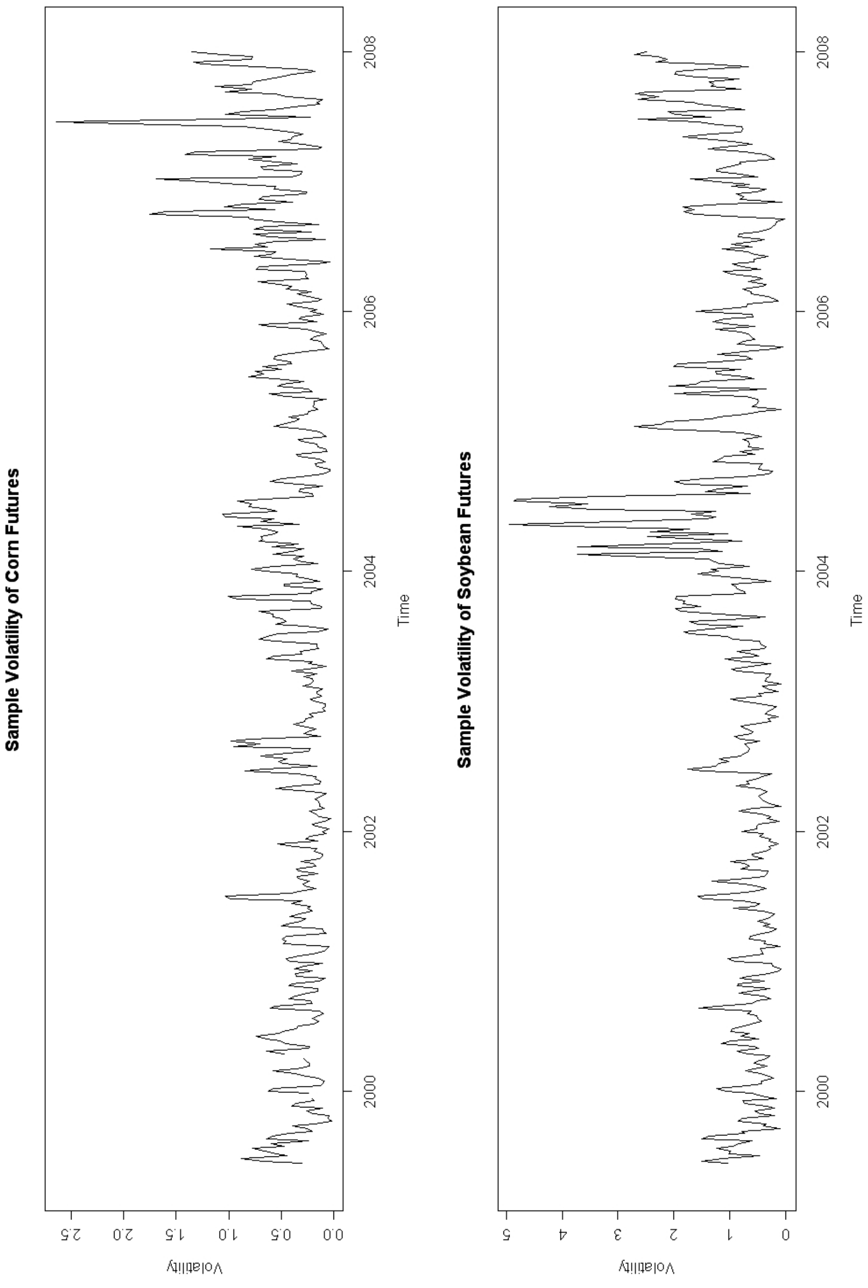

Figure 2: Corn and Soybean Futures Price Volatility: 06/1999 - 01/2008

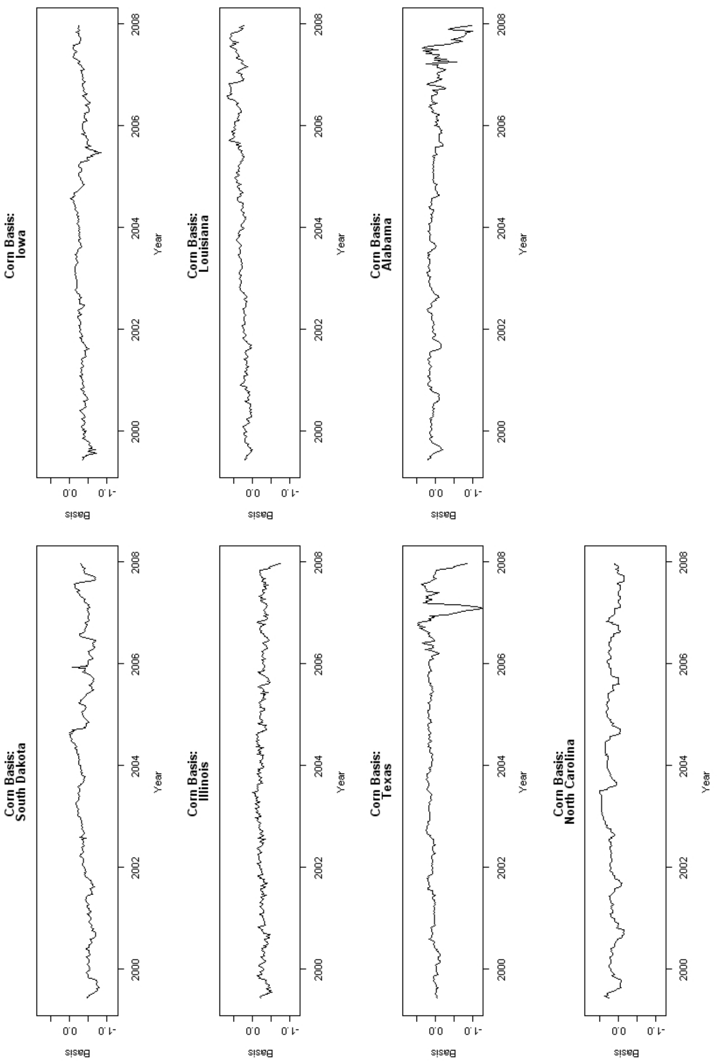

Figure 3: Corn Basis in Selected Markets: 06/1999 - 01/2008

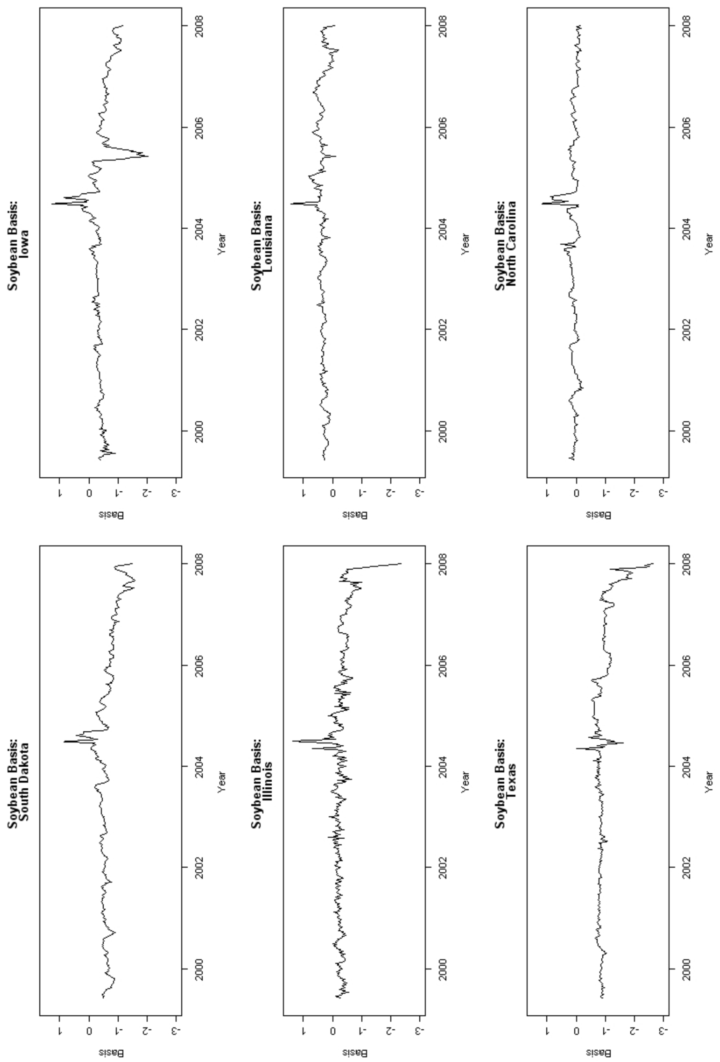

Figure 4: Soybean Basis in Selected Markets: 06/1999 - 01/2008

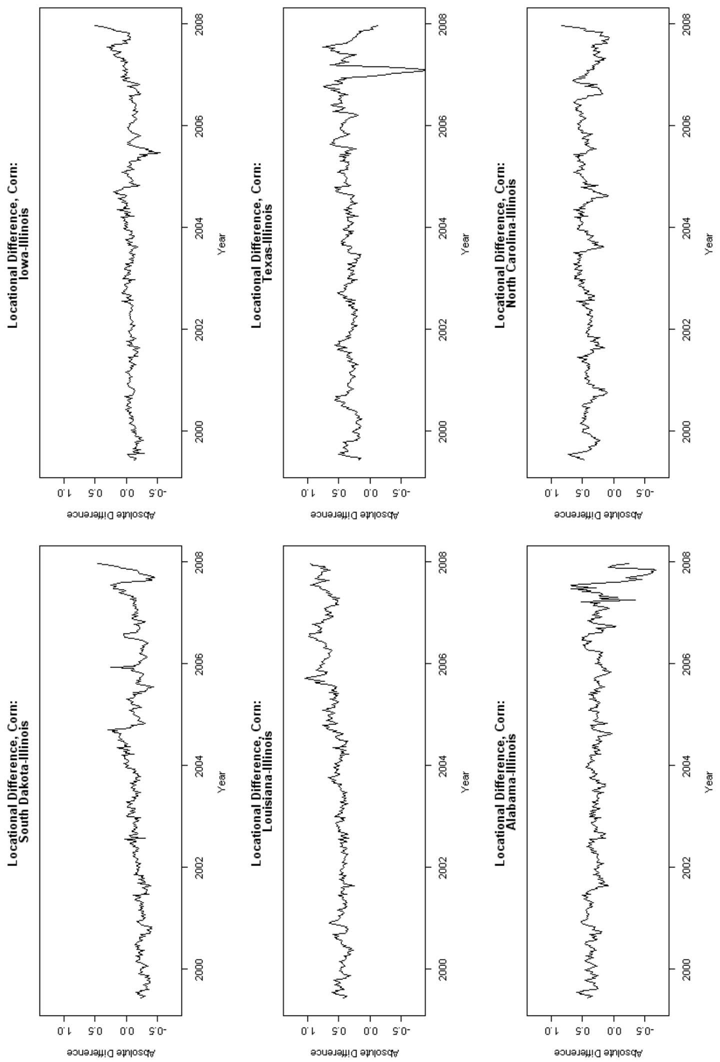

Figure 5: Absolute Differences in Basis for Selected Corn Markets

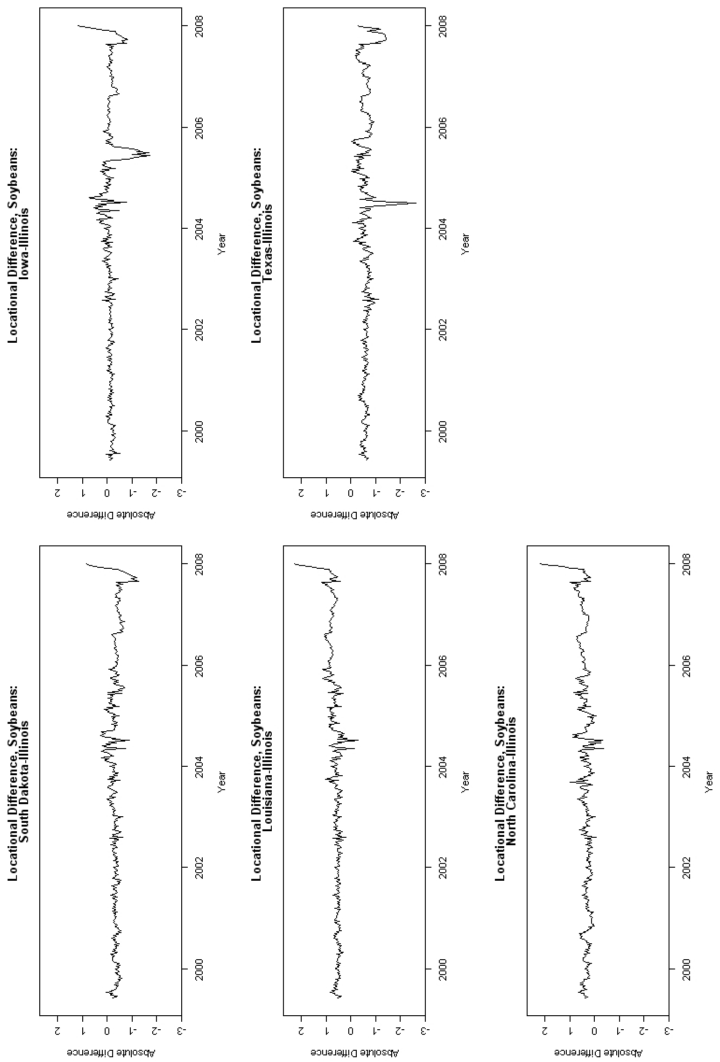

Figure 6: Absolute Differences in Basis for Selected Soybean Markets

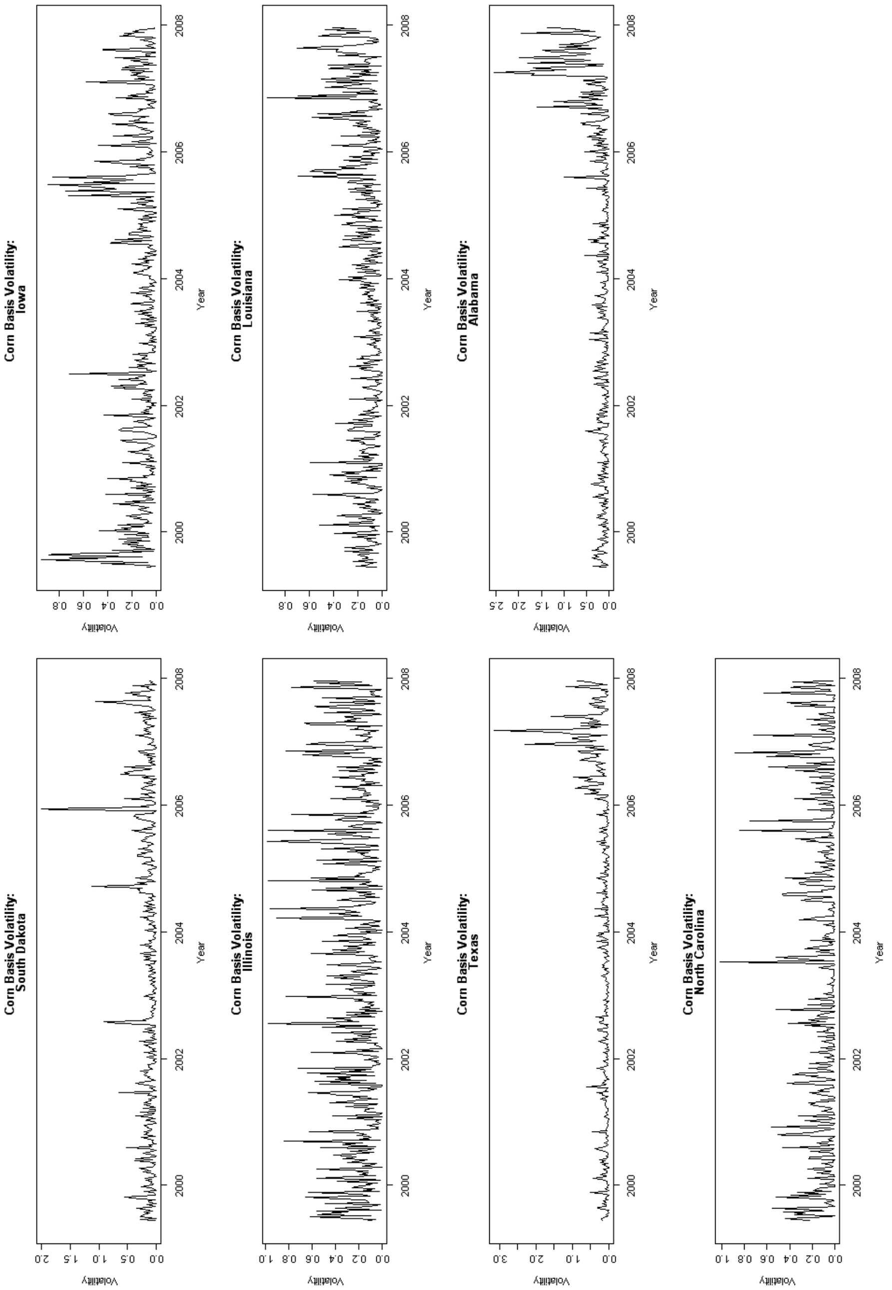

Figure 7: Corn Sample Basis Volatility in Selected Markets: 06/1999 - 01/2008

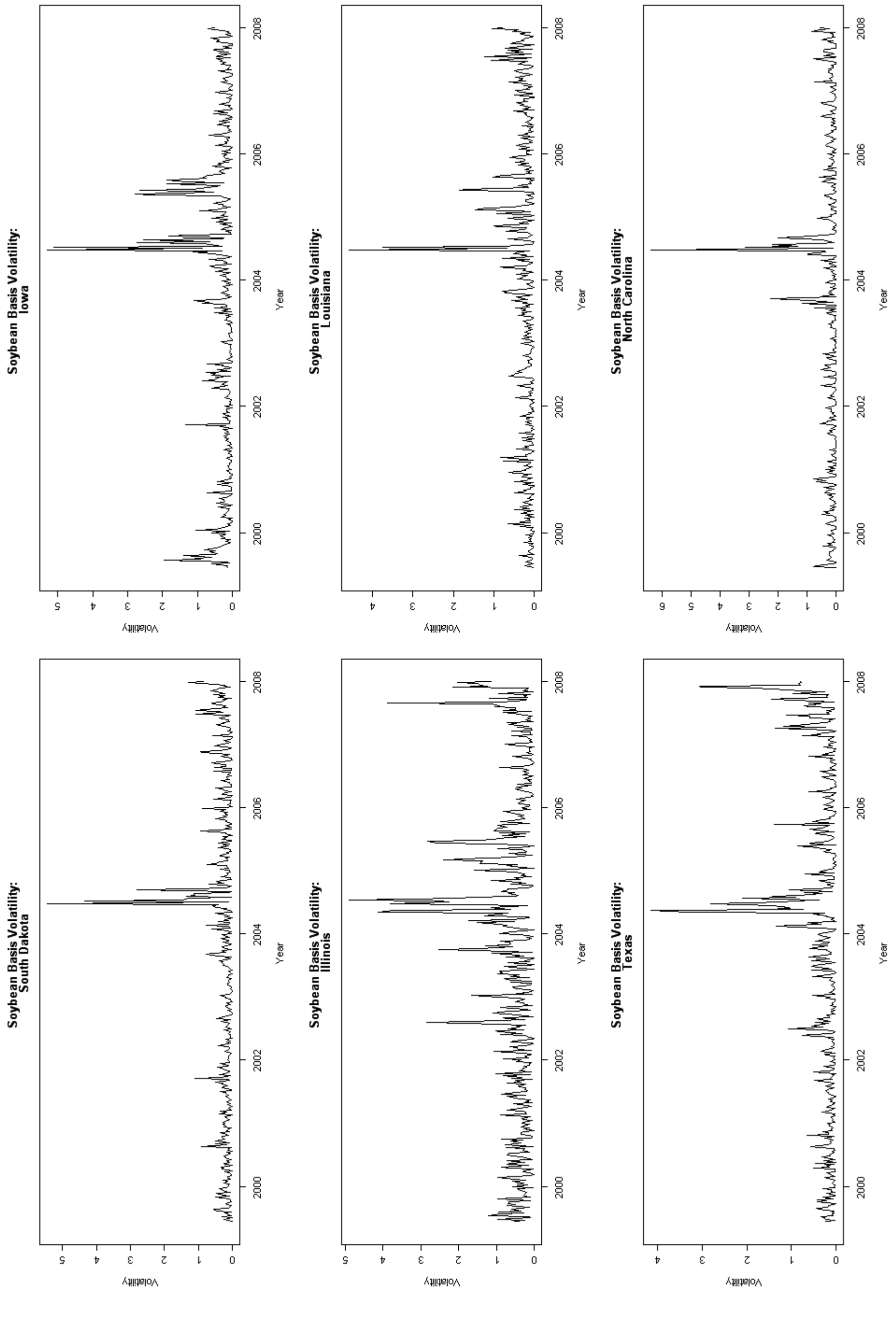

Figure 8: Soybean Sample Basis in Selected Markets: 06/1999 - 01/2008