Asymmetry, Risk, and Correlation Dynamics in the U.S. Fiber Market

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Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting Providence, Rhode Island, July 24-27, 2005

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Abstract

This study looked at the dynamics of conditional correlations and hedging strategies in the US main cotton producing regions. A two-step procedure was utilized to model, estimate, and analyze volatility, conditional correlations, and the optimal hedge ratios using spot prices in the Delta, Southeast, Southern Plains, and the Southwest regions and the New York commodity exchanges December futures contracts. The results indicate that volatilities in most of the regions are asymmetric and persistent. The derived conditional correlations and the optimal hedging ratios are dynamic although they do not have unit root. Moreover, the changes in agricultural policies altered the dynamics of correlations and producers' hedging strategies in the Delta, Southeast, and Southern Plains regions.

Key Words: Cotton, volatility, asymmetry, multivariate conditional correlations, and optimal hedge ratios

JEL Classification: C32, Q11

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Introduction

Effective risk management strategies are critically important under a volatile production and marketing environment. In that regard, hedging in the futures market is one of the mechanisms producers frequently use to cope with risk and uncertainties in the cash market. This instrument relies on a good understanding of the behavior of both the spot and the futures markets. Improved predictions of the spot and futures market volatilities and their dynamic relationships are critical for an efficient risk management strategy.

The most common tools used to measure price risks are derived from the family of autoregressive conditional heteroskedasticity (ARCH) models. These models provide a framework to measure volatility (i.e., risk) as a function of time and additional variables including lagged endogenous variables and exogenous variables (Nelson). The family of ARCH models has been expanded to a multivariate framework to measure volatility transmission between different sectors. Although the superiority of multivariate generalized autoregressive conditional heteroskedasticity (GARCH) models to analyze volatility between markets is widely accepted, their use is often hampered by procedural constraints such as a high number of parameters. Bollerslev (1990) developed the constant conditional correlation (CCC) GARCH model, which became popular and widely used in many studies on volatility of interdependent markets. The CCC model circumvents most of the procedural constraints observed in existing multivariate GARCH models. However, the assumption of constant correlations is increasingly untenable because conditional correlations between markets are likely to change overtime as new information becomes available. Engle recently proposed a more flexible multivariate model referred to as a dynamic conditional correlation (DCC) model. This multivariate model nests the

CCC model and provides a framework to test whether the correlations between markets are constant or not. The estimation approach follows a two-step procedure in which univariate GARCH models are estimated first. In a second step, the residuals from the conditional means are standardized to estimate the parameters of the conditional correlation equations. Since the evolution equations have the same structure for all correlations, the DCC models present the advantage of saving parameters compared to other multivariate GARCH models.

The derivation of correct univariate GARCH models is central to this modeling strategy. A correct univariate GARCH modeling should account for the asymmetric response of volatility price changes and the kurtotic nature of their underlying error term structure. As Nelson indicated, higher level of volatility is associated with “bad news” and lower level of volatility to “good news”. Black first described this asymmetric process, which also is known as the leverage effects. Moreover, a correct univariate GARCH model should also account for the kurtotic nature of price series, as volatility estimations are sensitive to the underlying structure of the error term. Studies on price volatility have relied on the assumption of a normally distributed error term structure, although it has been well documented that spot prices and futures prices tend to exhibit a leptokurtotic distribution. As Baillie and Myers reported, knowledge about the underlying distribution of price changes is critical for a successful hedging strategy. Bollerslev (1987) proposed a t-distributed error term GARCH model (GARCH-t) as an alternative to deal with excess kurtosis while modeling both conditional heteroskedasticity and non-normality. Baillie and Myers applied the GARCH-t in the determination of an optimal futures hedge, while Yang and Brorsen used it to analyze the dynamics of daily cash prices. While the GARCH-t outperformed the N-GARCH in both studies, its failure to account for the asymmetric distribution of the error terms was viewed as a disadvantage by the authors.

Under the assumption of normally distributed error, meaningful results can be obtained by using the quasi-maximum likelihood estimation (QMLE) (Bollerslev and Wooldridge). However, the QMLE is not efficient when the underlying error term is not normal. The proposed univariate models follows Nelson approach and fully accounts for the well established kurtotic characteristic of prices by applying a non-normal error term structure in volatility modeling based on the generalized error distribution to obtain estimates of cotton spot and futures price volatilities. Furthermore, the asymmetric nature of volatility is fully accounted in the univariate estimation while more flexibility is gained with the exponential GARCH (EGARCH) model. The EGARCH specification circumvents the constraints imposed on the parameter estimates that often impede the convergence of the traditional GARCH model.

The univariate EGARCH and multivariate conditional correlation models are estimated by maximum likelihood. The likelihood function in the multivariate case is greatly simplified by a reparametization of the conditional covariance matrix using the Choleski decomposition (Pourahmadi; Tsay). The derived time varying conditional correlations and conditional volatility between various segments of the U.S. fiber market determine the optimal hedge ratios (OHR). Following Kroner and Ng, the OHR represents the proportion of the position a risk-minimizing producer/investor takes in the futures market to hedge against an exposure in the spot market. Thus, it is an excellent tool to gauge producer or investor’s risk management strategies. The OHR and the correlation dynamics between markets are further analyzed to identify any structural breaks that may result from changes in U.S. agricultural policies and whether producers altered their hedging strategies following the adoption of new farm policies.

Methods

The study seeks to measure volatility between different spot markets in the U.S. cotton belt and between these spot markets and the December futures contracts. The approach follows a two-step process necessary to reduce the parameters constraints observed in multivariate methods. First, univariate GARCH models are estimated to generate the conditional volatility in each market. Second, these univariate volatility estimates enter the formation of the covariance matrix used in the multivariate model. There may be some loss of efficiency as described by Engle, but the method is fully consistent even under non-normality condition because the estimation of the likelihood function is based on the normalized residuals. A variant of Nelson exponential generalized conditional heteroskedasticity (EGARCH) models was specified. Under this specification, the volatility equation is in logarithmic format to circumvent the convergence problems generally observed in GARCH models because of constraints imposed on the parameters. The univariate EGARCH models are specified as follows:

(1) $y_t = \phi_0 + \sum_{k=1}^{r} \phi_i y_{t-i} + \varepsilon_t$ with $\varepsilon_t \mid \Omega_{t-1} \sim GED(\nu)$

(2) $\log\left(\sigma_t^2\right) = \theta_0 + \sum_{j=1}^{q} \beta_j \log\left(\sigma_{t-j}^2\right) + \sum_{i=1}^{p} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}}$

In this specification, equation (1) represents the conditional mean specified as an autoregressive model of order r, Ω_{t-1} is the information set at $t-1$, the error terms are assumed to follow a generalized error distribution (GED) with zero mean and variance σ_t^2. The specification is flexible in that the GED distribution nests several distributions, including normal, student-t, double exponential, and Laplace. It is also well suited to leptokurtotic series, which is characteristic of price series Nelson. Equation (2) represents the conditional variance equation for each market. The specification accounts for the volatility clustering observed in volatility behavior following exogenous shocks through the parameters α_i. It also accounts for the presence of leverage effects through the parameters γ_k. Lastly, the model accounts for persistence through the parameters β_i. The univariate EGARCH models specified above are estimated by maximum likelihood procedure. The probability density function of the underlying normalized error term $z_t = \varepsilon_t / \sigma_t$ is specified as follows:

(3) $$f(z_t) = \frac{\nu \exp\left[-\left(\frac{1}{2}\right)\left|z_t/\lambda\right|^{\nu}\right]}{\lambda 2^{(1+1/\nu)}\Gamma(1/\nu)}, \quad -\infty < z < \infty, \text{ and } 0 < \nu \leq \infty$$

(4) $$\lambda = \left[\frac{2^{(-2/\nu)}\Gamma(1/\nu)}{\Gamma(3/\nu)}\right]^{1/2}$$

From the specified probability density function, the parameters of the conditional mean, conditional variance, and the GED parameters are estimated using the likelihood function specified as

(5) $$L_T = T\left\{\log(\nu/\lambda) - (1+\nu^{-1})\log(2) - \log\Gamma(1/\nu)\right\} + (-1/2)\sum_{t=1}^{T}\left|\varepsilon_t/\lambda\sigma_t\right|^{\nu} + (-1/2)\sum_{t=1}^{T}\log(\sigma_t^2)$$

The second step is to formulate a multivariate conditional correlation model based on the derived volatilities. First, let us assume that the stationary price vector $\mathbf{y_t}$ follows a multivariate generalized error distribution with a corresponding vector of innovation $\boldsymbol{\varepsilon}_\mathbf{t}$ such that $\boldsymbol{\varepsilon}_\mathbf{t} \sim GED(0, \boldsymbol{\Sigma}_\mathbf{t})$. Thus, the conditional covariance matrix of the stationary price vector can be written as $\boldsymbol{\Sigma}_\mathbf{t} = \sigma_{ij,t}$ using the volatilities derived from the univariate models. Second, following Tsay, the matrix $\boldsymbol{\Sigma}_\mathbf{t}$ can be decomposed using the Choleski transformation such that

$\mathbf{\Sigma_t} = \mathbf{L_t G_t L_t'}$ where $\mathbf{L_t}$ is the lower triangular matrix with diagonal elements equal to one and off diagonal elements equal to $q_{ij,t}$ with $i \neq j$ and $\mathbf{G_t}$ is a diagonal matrix with diagonal elements equal to $g_{ii,t}$ and off-diagonal elements equal to zero. Under the Choleski decomposition, the vector $\boldsymbol{\varepsilon}_\mathbf{t}$ (i.e., vector of residuals from equation (1)), is orthogonally transformed into the vector $\mathbf{b_t}$ such that:

(6) $\varepsilon_{1,t} = b_{1,t}$

(7) $\varepsilon_{i,t} = q_{i1,t}b_{1,t} + q_{i2,t}b_{2,t}......q_{i(i-1),t}b_{i-1,t} + b_{i,t}$ with $1 < i \leq k$.

The residuals derived from the maximum likelihood estimation of the respective univariate EGARCH models are asymptotically normal although the generalized error distribution were considered in the specification. This is based on the asymptotic properties of maximum likelihood procedure as described in Nelson. Thus, the orthogonal transformations of these residuals are also normal, that is $\mathbf{b_t} \sim N(0, \mathbf{G_t})$. This property simplifies the log of likelihood function because the matrix $\mathbf{G_t} = diag(g_{ii,t})$ is positive definite if $g_{ii,t} > 0$. The dynamic conditional correlations are derived from the estimated variances of the transformed residuals and the equations of motion of $q_{ij,t}$ (the off-diagonal elements of $\mathbf{L_t}$), all of which are specified as follows:

(8) $\rho_{ij,t} = \sigma_{ij,t}\left(\sigma_{ii,t}\sigma_{jj,t}\right)^{-1/2}$ with $i \neq j$

(9) $\sigma_{ij,t} = \sum_{v=1}^{j} q_{iv,t}q_{jv,t}g_{vv,t}$ with $i > j$ and $i = 2....k$

(10) $\sigma_{ii,t} = \sum_{v=1}^{i} q_{iv,t}^2 g_{vv,t}$ with $i = 1.....k$

(11) $q_{ij,t} = w_{ij,0} + w_{ij,1} q_{ij,t-1} + w_{ij,2} \varepsilon_{j,t-1}$.

In this specification, equations (8) though (10) are, respectively, the dynamic conditional correlation, covariances, and variances equations. Equation (11) is the equation of motion or evolution equation; it is based on the lower triangle of the matrix derived from the Choleski decomposition of the variance covariance matrix. The parameters of the equation of motion are simultaneously estimated by maximum likelihood technique. It is important to note that the equation of motion dictates the dynamics of the correlation between markets overtime. Thus, the null hypothesis of constant conditional correlation versus the alternative of dynamic conditional correlation is tested by H_0: $w_{ij,1} = w_{ij,2} = 0$ vs. H_A: $w_{ij,1} \neq 0$ and/or $w_{ij,2} \neq 0$. The log likelihood function is defined as:

$$\ell\left(\mathbf{b_t}; w_{ij,0}, w_{ij,1}, w_{ij,2}\right) = -\frac{1}{2}\sum_{i=1}^{k}\left[\ln\left(g_{ii,t}\right) + \frac{b_{it}^2}{g_{ii,t}}\right].$$

The volatility derived from the univariate EGARCH and the correlation estimates between the spot and the futures derived from the DCC model are used to compute the time-varying optimal hedge ratios. Under the efficient market hypothesis, the optimal hedge ratio (OHR) defined as the ratio of the conditional covariance between the futures and spot price to the variance of the futures price is the number of futures contracts that a risk-averse investor is willing to hold in his portfolio (Baillie and Myers). The OHR and the correlation dynamics between markets are further analyzed to identify any structural breaks resulting from changes in U.S. agricultural policies and whether cotton producers altered their hedging strategies following the adoption of new farm policies.

Data consideration

This study uses data compiled from Agricultural Prices compiled by Agricultural Marketing Service (AMS) of the U.S. Department of Agriculture and the National Cotton Council of America (NCCA), which collects and summarizes information on futures contracts. The series comprise monthly averages spot prices for the Southeast (Alabama, Georgia, North Carolina, and South Carolina), Delta (Missouri, Arkansas, Mississippi, and Tennessee), Southern Plains (Texas and Oklahoma), and the Southwest (California and Arizona) and the December futures contracts for cotton from January l979 to December 2004. The December futures contracts were chosen because they are closer to harvest time. All price series were seasonally adjusted using a standard centered multiplicative moving average procedure available in Eviews. Franses and Paap have criticized the systematic filtering of economic series to remove the effects of seasonality and proposed the periodic time series approach. To our knowledge, unless the focus is directly modeling the trend and the seasonal components, using periodic time series modeling in a multivariate framework is not warranted in this context because it involves a complicated process and the results are difficult to interpret (Franses and Paap).

The results on the descriptive analysis of the data indicate the spot prices are all negatively skewed and positively kurtotic (Table 1). The skewness statistics were between (-0.39 for the Southern Plains spot price, -0.68 for the Delta spot price, and -0.56 for the futures contracts. The degree of kurtosis was between 3.02 for the Southern Plains spot market and 5.64 for the Southwest spot market. The Jarques-Bera probabilities for all series indicate a strong departure from normality. The moderate degree of kurtosis is indicative of presence of small price movements over the sample period, while the negative skewness shows the predominance of downward spikes. These dynamics are consistent with an uncertain domestic fiber market subject to shocks from various sources (Cashin and McDermott, 2002). The data was transformed into a log format for the remaining of the study. Augmented Dickey Fuller (ADF) test suggest the presence of unit roots for the Delta, Southeast, and the Southern Plains regions, the analysis of the correlograms of the three series, however, shows that they were indeed stationary and could be modeled as autoregressive of order 1 as indicated by the behavior of their respective partial autocorrelation function. Thus, these series were used at their level and modeled as autoregressive of order 1, while autoregressive models of order 4 and 1 were used for the futures price and the Southwest spot price series.

Empirical Results

The results of the univariate EGARCH are summarized in Table 2. All models were estimated using EGARCH(1,1). The results on the conditional mean confirm that the price series are indeed stationary although showing some degree of persistence. The sum of the parameters estimated on the autoregressive component is less than one for all prices.

The results on the conditional variance focus mainly on the volatility clustering asymmetry, persistence, and non-normality parameters. The results show evidence of significant volatility clustering in the Delta, Southern Plains and Southwest regions as the parameter α_1 was positive and significantly different from zero in these regions. Thus, for these regions, larger shocks, whether positive or negative, are followed by larger changes in volatility. The asymmetric coefficient (γ_1) is significant and negative for the Delta, Southeast, and Southern Plains regions and the futures markets. Thus, spot prices in these regions and the December futures contracts react differently to "good news" versus "bad news". The negative sign on the parameter γ_1 indicates that for these markets as well as for the futures market, negative shocks are followed by increased volatility level, while positive shocks tend to result in lower volatility level. The results show high degree of volatility persistence in the Southeast, Southern Plains, and Southwest region as indicated by the magnitude of the parameter β_1. The calculated half-life decay estimated by $\log(0.5)/\log(\beta_1)$ is 43 months in the Southeast, 11 months in the Southern Plains, and 6 months in the Southwest. Thus, while shocks in these markets tend to persist, shocks in the futures and the Delta spot markets tend to be short-lived. Thus, the Delta spot market appears to be more efficient than the remaining spot markets because any deviation from its competitive equilibrium dissipates rapidly.

The non-normality parameter is also significant indicating that the error term structure used in the univariate EGARCH models is appropriate. The parameter estimates, which are all less than 2 show that cotton spot and futures prices have thicker tails than the standard normal distribution. The diagnosis parameters based on the Ljung-Box autocorrelation tests on the residual and squared residuals show that the variable specifications are appropriate as the test fails to reject the null of no autocorrelated residuals. As for residual non-normality, it is clear that the GED does not transform the residual into normally distributed residuals. Thus, the remaining inference and estimation are solely based on the asymptotic properties of the maximum likelihood procedure as previously indicated.

The analysis in this section focuses on the derived correlations. The description of the results pertaining to the equations of motion and their implications in terms of the nature of conditional correlation between markets are presented first. As Table 3 indicates, the constant conditional correlation is rejected in all interrelationships except for the Futures and the Southwest spot markets, Delta and the Southwest, and Southern Plains and the Southwest. The markets where constant correlation may be appropriate are associated with the Southwest spot market. The reason for this remains unclear. The remaining discussion focuses only on markets that are dynamically related.

Stationarity tests based on the ADF method were conducted on the derived conditional correlation series. The results show a rejection of the null of unit root for all correlation series. Thus, while the conditional correlations show some variability over the sample period as indicated by the statistical test on the parameters of the equation of motion, the absence of unit root in all series is an indication of stable relationships within spot markets and between spot and futures markets. The conditional correlations are tested for persistence and presence of deterministic trend and structural breaks that may be the effect of changing agricultural policies. The results of these statistical tests are summarized in Table 4.

As Figure 1 indicates, the conditional correlation between December futures contracts and the Delta spot price shows an upward trend interrupted by periods of low relationship for the 1986-1987, 1994-1995, and 2002-2003 periods. The relationship is moderately persistent as indicated by an autoregressive parameter estimated at 0.61. Moreover, there is significant difference between the *1996 Farm Policy* and the policies adopted in 1980, 1985, and 2002 regarding their contribution to the correlation between the December futures and the Delta spot price. Correlation between the futures and the delta spot markets became higher after the adoption of the *1996 Farm Bill*.

The conditional correlation between the Southeast spot prices and the December futures contracts is relatively low and show no noticeable trend, fluctuating between -0.1 and 0.4 (Figure 2). A significant break occurred in 1996 as indicated by a positive and significant parameter for the *1996 Farm Bill*. The correlation between Southeast and the Delta spot markets was relatively high prior to 2002, averaging 0.62 with occasional spikes that reach 0.9 (Figure 3). However, after the adoption of the *2002 Farm Bill*, the correlation between the two markets despite their geographical proximity dropped to as low as 0.3 with a no persistence. Compared to the previous policies, the *2002 Farm Bill* contributed to 9.5% decrease in the correlation between the two markets.

The correlation between the Southern Plains and the December futures contracts is relatively low, averaging 0.28. Although not perceptible in Figure 4, the correlation between the Southern Plains spot market and the December futures contracts has trended down over the sample period and has been sensitive to the changes in agricultural policies. Despite a low persistence, three structural breaks did occur to alter the path of the conditional correlation. The statistical significance and the positive sign of the parameters of the *1985, 1996,* and *2002 Farm Bill* indicate that the policies changes have contributed to increased level of correlation between the Southern Plains spot market and the December futures contracts.

Figures 5 and 6 illustrate the dynamic of the correlation between the Southern Plains and the Delta spot markets and between the Southern Plains and the Southeastern spot markets. These two correlations have similar path, which was expected, considering the proximity of the two regions. Further analysis based on the results on Table 4 indicates that although the correlation between Southern Plains and the Southeast spot moderately trended downward, the degree of persistence and the effects of policy changes on the correlation are similar. The agricultural policies adopted in 1985 and 1996 significantly increase the correlations between the Southern Plains and the Delta spot markets and between the Southern Plains and the Southeastern spot markets.

Similar to the derived dynamic conditional correlations, stationarity tests based on the ADF find no unit root in the optimal hedge ratios across all regions. Thus, despite some variability, producer's hedging strategies appear relatively stable over the sample period. All the hedge ratios were less than one. A risk-minimizing producer in the Delta region, on average, shorts 30¢ worth of futures position to hedge against a $1 long position in the cash market. However, as Figure 8 illustrates, the OHR appears trending upward between 1994 and 2002 although the parameter on the trend component was not significant (Table 5). Moreover, it is persistent and responsive to the *1996- and 2002 Farm Policy*. In the Southeast, the OHR shows no discernable pattern (Figure 9) although it has increased because of the *1996 Farm Policy* (Table 5). The average OHR amounted to 0.25 in the Southeast region. The OHR in the Southern Plains fluctuates considerably between 0.20 and 0.40 showing no discernable trend. However, there were three structural breaks after the adoption of the *1985-, 1996, and 2002 Farm Policy*. In the Southwest, OHR shows a high degree of persistence fluctuating between 0.20 and 0.60 for the most part (Figure 11) with an average 0.41.

Conclusion

This study applies a flexible multivariate conditional correlation approach to estimate price volatility and derive the conditional correlations and hedge ratios in the U.S. main cotton-producing regions. The results confirm the asymmetric nature of volatility transmission in the futures market, the Delta, Southeast, and Southern Plains spot markets and the lasting effects of shocks in all but the Delta region. The results of the dynamic estimation clearly show that the hedge ratios and the correlation associated with the Southwest production region are less prone to change over time. The resulting hedge ratios in most cases have increased under the *1996 Farm Policy*, while the *2002 Farm Policy* appears shifting OHR in the Delta. Producers in the Southern Plains reacted to all policy changes with a noticeable impact of the *1996 Farm Policy*.

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Table 1. Descriptive Statistics of Cotton Spot and Futures Prices (¢/Lb.) in the U.S. Main Production Regions 1979-1980

	Futures	Delta	Southeast	Southern Plains	Southwest
Mean	76.86	69.36	71.35	64.38	75.75
Maximum	104.30	100.23	102.17	97.48	127.66
Minimum	38.62	29.78	34.55	33.31	39.58
Std. Dev.	12.71	12.00	12.48	11.91	12.83
Skewness	-0.56	-0.68	-0.52	-0.39	0.01
Kurtosis	3.12	4.51	3.61	3.02	5.64
Probability	0.000	0.000	0.000	0.018	0.000
Observations	312	312	312	312	312

Notes: The probability refers to the P-value of the null hypothesis of normality using the Jarque-Bera method. The kurtosis and skewness parameters are compared with their corresponding values under normality, which are 0 and 3, respectively.

Table 2. Univariate EGARCH Model Estimation Results

Parameters	Futures	Delta	Southeast	Southern Plains	Southwest
			Mean Equation		
ϕ_0	0.269***	0.126***	0.233	0.249	0.292***
	(0.083)	(0.056)	(0.079)	(0.083)	(0.091)
ϕ_1	1.192***	0.970***	0.945	0.940	0.932
	(0.061)	(0.013)	(0.018)	(0.020)	(0.021)
ϕ_2	-0.331***	--	--	--	--
	(0.100)				
ϕ_3	0.243**	--	--	--	--
	(0.095)				
ϕ_4	-0.167***	--	--	--	--
	(0.060)				
			Variance Equation		
θ_0	-1.765**	-3.517***	-0.113	-0.488**	-0.823*
	(0.819)	(1.091)	(0.105)	(0.241)	(0.463)
α_1	0.026	0.393**	0.031	0.199**	0.302***
	(0.104)	(0.178)	(0.033)	(0.092)	(0.043)
γ_1	-0.262***	-0.177**	-0.069**	-0.101*	0.005
	(0.102)	(0.108)	(0.031)	(0.059)	(0.059)
β_1	0.703***	0.448**	0.984***	0.939***	0.889***
	(0.133)	(0.179)	(0.016)	(0.038)	(0.077)
ν	1.749***	1.272***	1.610***	1.564***	1.297***
	(0.210)	(0.120)	(0.181)	(0.215)	(0.181)
			Diagnostic Parameters		
LLF	484.310	475.626	468.861	428.536	410.117
Q(10)	9.805	5.241	5.130	5.906	8.631
Q2(10)	5.381	3.384	3.335	5.003	16.043
Normality	10.205	13.261	7.506	13.378	35.138

Notes: The symbols ***, **, and * indicate statistical significance at the 1-, 5-, and 10-percent levels. The values between the parentheses represent the standard errors of the parameter estimates.

Table 3. Evolution Equation Estimation Results

	Futures	Delta	Southeast	Southern Plains
Delta	0.242***	--	--	--
	(0.092)			
	0.516***	--	--	--
	(0.179)			
	3.097**	--	--	--
	(1.306)			
Southeast	0.049	0.548***	--	--
	(0.049)	(0.158)		
	0.798***	-0.394	--	--
	(0.196)	(0.313)		
	-0.675	2.967**	--	--
	(0.825)	(1.371)		
Southern Plains	0.000	0.047	0.495***	--
	(0.010)	(0.062)	(0.126)	
	0.869***	0.844***	-0.686***	--
	(0.133)	(0.194)	(0.205)	
	0.777	-0.451	-1.239	--
	(0.600)	(0.553)	(0.885)	
Southwest	0.373	0.503	0.004	0.369**
	(0.375)	(0.408)	(0.007)	(0.170)
	0.253	-0.324	0.991***	-0.307
	(0.749)	(1.013)	(0.017)	(0.458)
	-0.876	-1.114	-0.005	0.997
	(0.840)	(1.661)	(0.280)	(1.278)

Notes: The symbols *** and ** indicate significance at the 1- and 5-percent levels, respectively. The standard errors are between parentheses.

Table 4. OLS Estimates of the Dynamics of Conditional Correlation

	Delta-Futures	**Southeast-Futures**	**Southeast-Delta**	**Southern Plains-Futures**	**Southern Plains-Delta**	**Southern Plains-Southeast**
Constant	0.103***	0.648***	0.349***	0.231***	0.169***	0.193***
	(0.015)	(0.018)	(0.029)	(0.020)	(0.024)	(0.027)
AR(1)	0.604***	-0.417***	0.334***	0.215***	0.537**	0.523***
	(0.055)	(0.064)	(0.051)	(0.063)	(0.068)	(0.069)
Trend×10^3	-0.047	-0.043	-0.016	-0.386***	-0.096	-0.183*
	(0.097)	(0.155)	(0.147)	(0.161)	(0.100)	(0.106)
1985 Farm	0.014	0.006	-0.021	0.044**	0.030**	0.025*
Bill	(0.012)	(0.021)	(0.019)	(0.021)	(0.014)	(0.014)
1996 Farm	0.033*	0.057*	0.007	0.093***	0.051**	0.046*
Bill	(0.019)	(0.043)	(0.028)	(0.034)	(0.021)	(0.022)
2002 Farm	0.037	-0.044	-0.095**	0.071*	0.016	0.026
Bill	(0.026)	(0.043)	(0.042)	(0.043)	(0.027)	(0.028)
R Squared	0.444	0.219	0.338	0.111	0.402	0.329

Notes: The chosen models were based on the results of the equation of motion. With regard to conditional correlations between the Southwest and the remaining regions, only the conditional correlation with the Southeast was modeled and none of the coefficient came out significant. The symbols ***,**, and * represent significance at the 1-,5, and 10 percent level. The values between parentheses are White heteroskedasticity-consistent standard errors

Table 5. OLS Estimates of the Dynamics of OHR

	Delta	Southeast	Southern Plains	Southwest
Constant	0.117***	0.236***	0.155***	0.206***
	(0.201)	(0.022)	(0.023)	(0.031)
AR(1)	0.534***	0.108	0.441***	0.541***
	(0.075)	(0.071)	(0.073)	(0.060)
Trend×10^3	-0.1666	-0.254	-0.628***	-0.082
	(0.208)	(0.255)	(0.258)	(0.244)
1985 Farm Bill	0.038	0.021	0.076**	-0.026
	(0.025)	(0.031)	(0.033)	(0.030)
1996 Farm Bill	0.079**	0.107**	0.151***	-0.050
	(0.041)	(0.047)	(0.055)	(0.049)
2002 Farm Bill	0.094*	-0.021	0.121*	-0.067
	(0.055)	(0.063)	(0.066)	(0.070)
R Squared	0.353	0.157	0.281	0.324

Notes: The symbols ***,**, and * represent significance at the 1-,5, and 10 percent level. The values between parentheses are White heteroskedasticity-consistent standard errors

Figure 1. Conditional Correlation between Delta and Futures

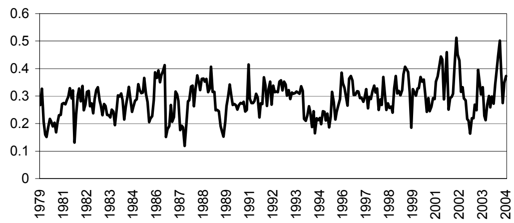


Figure 2. Conditional Correlation between Southeast Futures

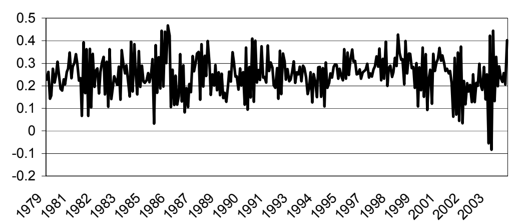


Figure 3. Conditional Correlation between Delta and Southeast

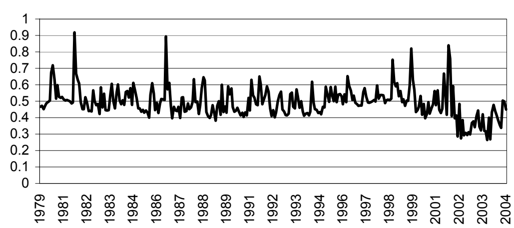


Figure 4. Conditional Correlation between Southern Plains and Futures

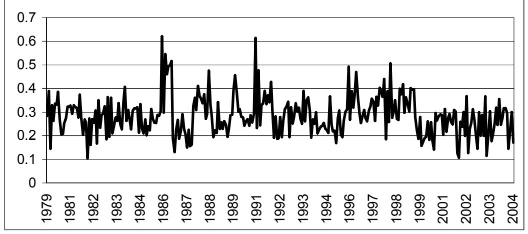


Figure 5. Conditional Correlation between Southern Plains and Delta

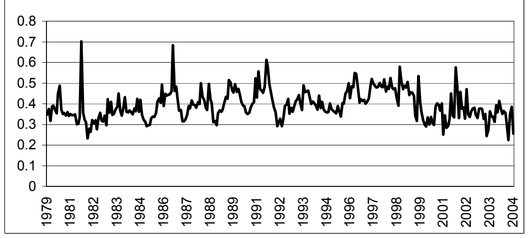
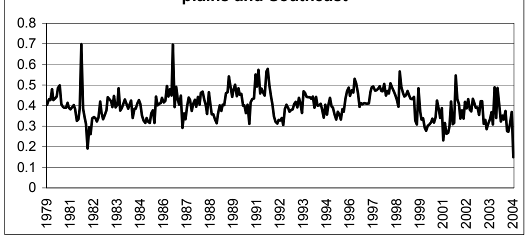


Figure 6. Conditional Correlation between Southern plains and Southeast



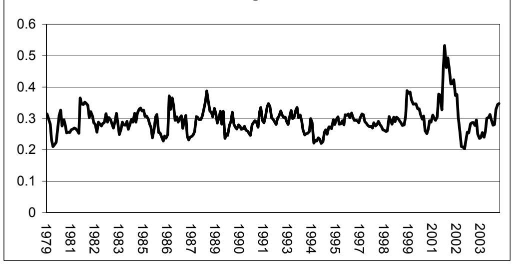


Figure 7. Dynamic Optimal Hedge Ratio in the Delta Region

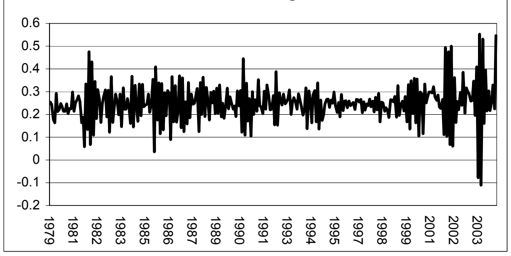


Figure 8. Dynamic Optimal Hedge Ratio in the Southeast region

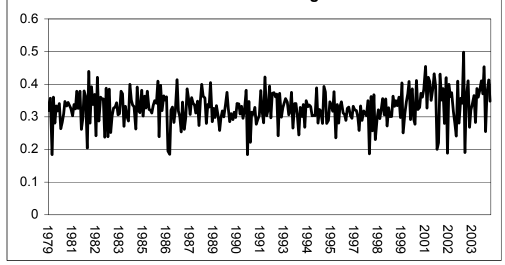


Figure 9. Dynamic Optimal Hedge Ratio in the Southern Plains Region

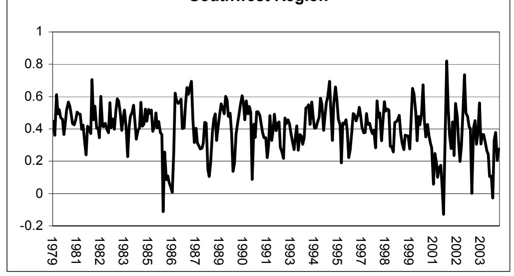


Figure 10. Dynamic Optimal Hedge Ratio in the Southwest Region