Risk Premia in FCOJ Futures Markets: A Thirty Year Perspective

Dean G. Fairchild
e-mail: dfairchild@fred.ifas.ufl.edu

Institute of Food and Agricultural Sciences
Food and Resource Economics Department

P.O. Box 110240
McCarty Hall B288
Gainesville, Florida 32609-0240

Applied Econometrics Field Paper
1997

Futures Contracts on FCOJ and Hedging Uses

The risk premium theory regarding futures markets is tested in the context of producer hedging in the FCOJ (Frozen Concentrated Orange Juice) futures market. This is a follow-up of Ward, Tuttell, and Fairchild's 1989 staff paper which tested the behavior of FCOJ prices from 1974-1984 using spot and futures price data in a simulation of possible hedges during a ten year period on each of the six maturity months. The original inquiry is expanded by enlarging the time series to the 1967-1996 period as well as considering alternative spot price measures.

Past work has centered in three areas: hedging strategies and performance, risk premium theory, and relative risk measures. The first area, FCOJ futures hedging strategies and performance are covered in detail in many Florida Department of Citrus publications (Ward, 1975). One of the key elements of any hedging program in futures concerns the basis, or difference between the cash price and futures price. According to Ward (p.43), "FCOJ basis consistently narrows from late fall to early spring and this is precisely when most short hedged positions are carried." Additional discussion of basis behavior in FCOJ futures is found in Ward and Dasse(1975) and Dasse(1975).

Because orange juice has smaller annual supplies (in relation to annual demand) and lower storability relative to other futures commodities such as precious metals and grains, there are likely to be frequent departures from the cost of carry model (Kolb, 1991, p.196). The cost of carry theory posits that distant futures prices will exceed nearby futures prices and the current cash price by the sum of costs (storage, insurance, opportunity costs, etc.). However, because of relatively tight FCOJ supplies and convenience yield (Working 1948), FCOJ futures frequently disobey the cost-of-carry pattern and, in extreme cases, the market becomes inverted. For this reason, some argue that the FCOJ futures market is not theoretically as well-behaved as the grains for example. Malick and Ward (1987) consider why arbitrageurs do not capitalize on certain reoccurring basis patterns.

Risk Premium Theory

Risk premium theory reasons that the FCOJ futures market may not reflect the full value of the concentrate traded because of the presence of a risk premium. The term risk premium comes from three areas of futures theory, storage risk premium, speculative risk premium (Ward and Dasse, 1977, p.72 fn.1) and option premium. Risk premium is used means that hedgers pay speculators a premium for accepting the transfer of price risk. Similarly, in storage, those who carry stocks through time face inventory risk and need to be compensated for transferring goods through time. Risk premium is also used in options theory when options prices are decomposed into time and intrinsic value. The time value of an in-the-money option is clearly a premium for transferring risk through time paid by the writer(seller) of a put or call option. The time-value of an out-of-the money option consists of the entire premium and compensates the seller for the risk that the buyer may be able to exercise the option in the future even though it has no value now.

When hedging with futures, rather than options on futures, the risk premium is not directly observed as in the case of an option.[1] A futures hedger merely compares the ratio of realized price to ending spot price to recover the premium (or discount). Suppose a short futures hedge k weeks in length was initiated at time t with the futures contract price of a particular maturity of FP_t. The realized price would depend on the sales price of concentrate in the cash market at the end of the hedge at time t+k, $SPOT_{t+k}$, and the closing futures price FP_{t+k}. Realized price (RP) then equals:

$$RP_{t+k}=S_{t+k}+(FP_t-FP_{t+k}) \tag{1}$$

or the ending spot price plus (or minus) the gain (or loss) on futures net of transactions costs.

A "relative gains" premium, PM then equals S_{t+k}/RP_{t+k}. PM is a simplistic way to show the market's performance at a particular time over the specified hedge length, k. If PM < 1, there are gains

[1] In reality, the option premium has embedded the price risk of the underlying futures contract, underlying commodity, and the price risk of the option itself which are technically three separate risk premia.

from the future's position, but if PM > 1, losses on the futures have occurred. For example, if the PM was 1.07 for a particular hedge, the realized price (RP) would be in fact discounted to the resulting spot price. In such a case, the market might be partly reflecting a risk premium because the futures price is discounted to the cash price. Here is a chart showing the PM observed in the 1967-1995 FCOJ price data. Note that both the mean and modal values suggest a possible risk premium.

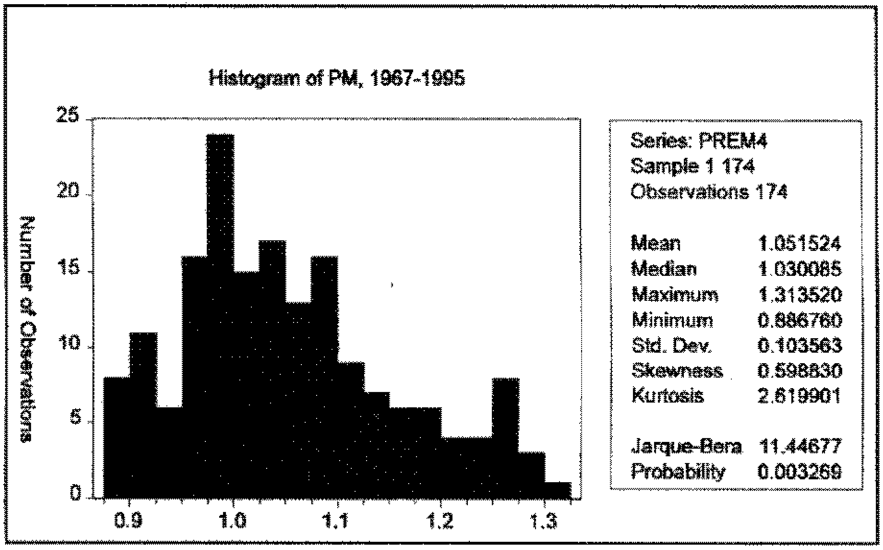

Figure 1, Possible Evidence of a Risk Premium?

One way of modeling the risk premium is to relate it as a function of the variability of the underlying spot price. With high variability, the premium would be higher than with lower variability to compensate speculators for the presumed higher risk that accompanies a higher variability. But what measure of dispersion should be used to capture the variability? Measures such as variance and standard deviation that depend on units of measure would be less sensible than the unit-free coefficient of variation (ratio of the standard deviation to the mean). Hence, the following risk premium function (using sample statistical notation) is posited:

$$PM = f(CV_{spot})$$
$$PM = f\left(\frac{s_{spot}}{\overline{X}_{spot}}\right)$$
$$where:$$
$$\overline{X}_{spot} = \Sigma_{i=1}^{n} \frac{SPOT_i}{n_{spot}}$$
$$s_{spot} = \Sigma_{i=1}^{n} \frac{[SPOT_i - \overline{X}_{SPOT}]^2}{n_{spot}-1}$$

(2) Risk Premium Function

The precise functional form is unknown, but following Ward, Tuttell and Fairchild the form could be a fourth-order polynomial expansion which could accommodate the expected theoretical pattern of PM increasing with higher levels of spot price variability.

Relative Risk Ratios

Another way to measure the risk of establishing futures positions is to define a relative risk ratio after Ward and Schimkat (1979). The relative risk (RR) for a particular futures short hedge is given by:

$$RR_{t+k} = \frac{Var[SPOT_{t+k} + (FUT_t - FUT_{t+k})]}{Var[SPOT_{t+k}]} \quad (3)$$

Note that a RR below 1 implies risk reduction while an RR over 1 suggests that hedging was poorly executed and/or that futures markets are performing incorrectly (Ward, Tuttell, and Fairchild, 1989, p.3).

Procedure

Existing data from the Ward, Tuttell and Fairchild study were used as a foundation for the analysis. In some cases, observations were missing or in error and were corrected where possible. New data brought the sample into early 1996. Three different spot prices were used in producer hedge simulations. Two involved the splicing of one data set with another because several prices were available for all or part of the thirty years. In fact, the lack of a single spot price readily comparable to the prices of the FCOJ futures led the ***Wall Street Journal*** and other sources to stop publishing cash prices. Since 1967, orange marketing and the structure of the citrus industry has changed markedly, leading to a less obvious "cash" price than the familiar grain elevator cash quotes for other agricultural commodities.

Consider the weekly price series available. First, a reasonably realistic spot price published by the Florida Canner's Association, SPOT [2], covered from January, 1967 to March of 1986. SPOT is based on the "delivered-in price" or the raw fruit price of unconverted oranges for juice delivered to processors. According to Ward and Dasse (1975, p.72) SPOT responds readily to changing market conditions. Because SPOT was discontinued over ten years ago, other price series were examined for comprehensive coverage of the entire time period.

A second series, SPOT2, is a final price per pound solids, combined, of oranges used in FCOJ (from FCA). SPOT2 covers the 1967-1996 period except it is not observed from late summer to mid-fall. Hence, there is no data for SPOT2 from early August into November. 1044 observations of the 1536 weeks from 1967-1996 were available for SPOT2.

A third series, FOBBLK, is the Florida FCOJ average bulk tanker FOB price, per pound solids from Florida Citrus Mutual. 629 observations in the 1536 weeks from 1967-1996 were available from late 1983. FOBBLK is slow-moving and does not react to market conditions as SPOT and SPOT2 do.

Because no single series was adequate, two series (SPOT3 and SPOT4) were constructed for simulation use. Additionally, SPOT2 was used in simulation as well. The first constructed series, SPOT3 was obtained by estimating SPOT2 from SPOT (FIGURE 2). There were 649 overlapping observations of SPOT and SPOT2 which enabled estimation of a linear regression of the derived series SPOT3.

---

[2] Capitals are used throughout to indicate variables used in the analysis.

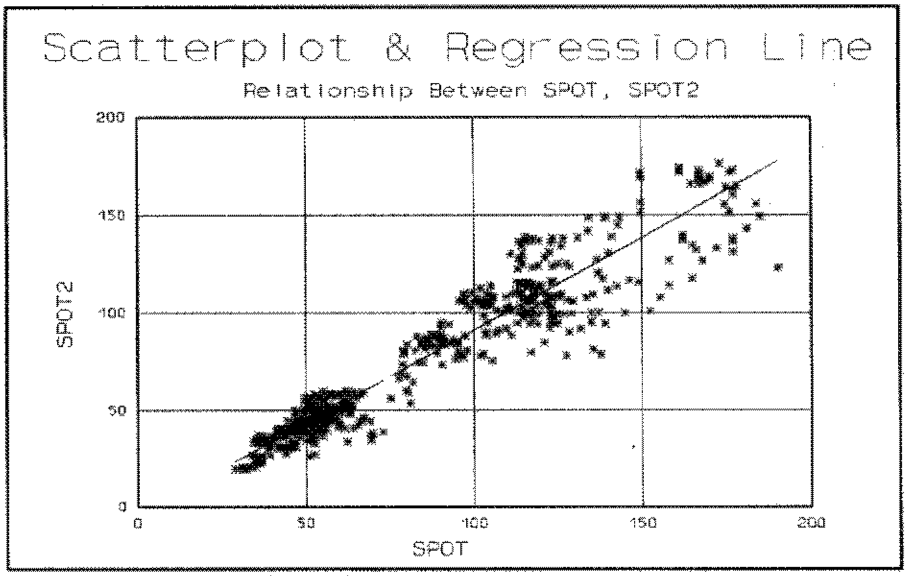

Figure 2, Derivation of SPOT3

SPOT3, the first derived series, consisted of all values of SPOT2 which were observed alone or together with SPOT (1044 cases) and predicted values of SPOT2 estimated based on the regression (257 cases) for a total of 1301 observations for SPOT3. SPOT4, the second derived series, was sequentially estimated in a similar way by regressing SPOT2 on FOBBLK (FIGURE 3).

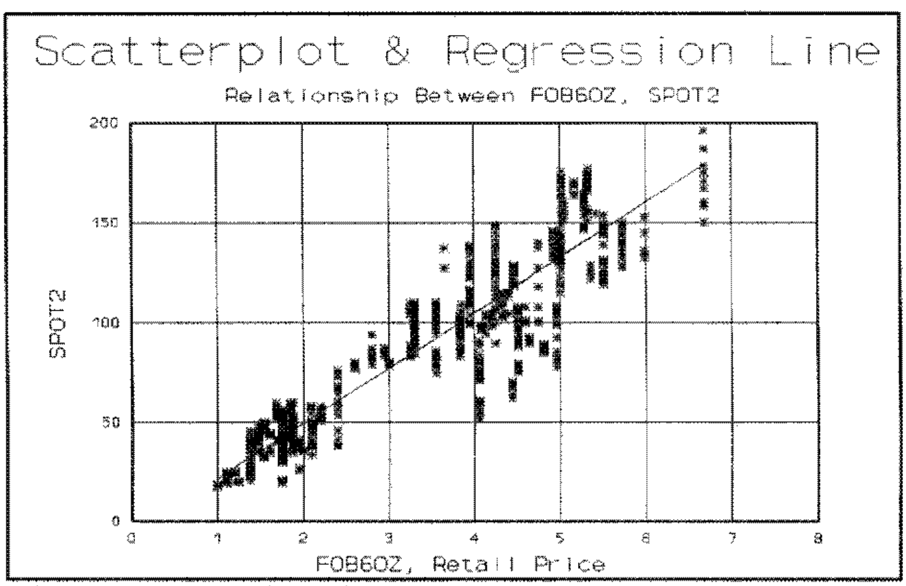

Figure 3, Derivation of SPOT4

Futures data from the original study were augmented by ***Wall Street Journal*** quotations and by downloading data from the New York Cotton Exchange's ftp site. Error checking of the old data and crosschecking yielded an accurate set of futures prices. Due to thin markets (especially in the early years), a futures price was not available for every contract each week. The sample size by maturity month was: January(1494), March(1466), May(1469), July(1487), September(1438), and November(1466).

Simulation

The scope of the project was large. If every possible simulation for every day over the thirty year period had been done, over 46,000 individual hedges would need to be simulated, figuring in the six available maturity months. The Ward, Tuttell, and Fairchild study varied hedge length from 4 to 16 weeks. Hence, 46,000 is multiplied by 13 to yield almost 600,000 possible positions.

The current study differed in two ways, both of which increased the number of possible hedges. First, hedge length was varied from 4 to 20 weeks, resulting in a multiplier of 17 rather than 13. Second, by using three different spot prices more than doubled the number of possible hedges. As in Ward, Tuttell, and Fairchild, only the Wednesday futures prices were selected, cutting the possible number of simulations by roughly eighty percent. This still left an approximate 477,000 possible hedges.

The actual number of simulated hedges was much lower, 361,034 owing to three factors which were carefully accounted for in the simulation program. First, missing futures data for days when hedges were opened or closed prohibited calculation. Second, missing spot price data for hedge close dates would not permit the calculation of PM. Third, contract expirations had to be controlled for.

Results

The objective was to quantify the proportion of the observed spot risk premium that could be explained by variation in the underlying spot prices. With the premium measure (PREM) serving as dependent variable, the independent variables were measures of the variability of the underlying spot price as measured by powers of the annual coefficient of variation of the spot price.

$$PM = B_0 + B_1 CV(SPOT) + B_2 [CV(SPOT)]^2 + B_3 [CV(SPOT)]^3 + B_4 [CV(SPOT)]^4 \quad (4)$$

The estimating equations(4) were used to estimate the relationship between SPOT2, SPOT3, and SPOT4 and the corresponding premium measure. The functional form above was chosen in Ward, Tuttell, and Fairchild. Final estimation made use of four terms, but used different exponents.

Three analytic areas were most important. First, regressions were run with rough replication of the 1989 results in mind to ensure that the simulations had proceeded along the right track even though the simulations differed. Second, multiple regressions of (4) involving the full data set were run. Third, due to serious multicollinearity, principal components regressions formed the final stage of analysis.

Replication

Precise replication with the 1989 work could not take place for several reasons. When possible, errors and omissions in the original data were corrected, resulting in a new set of numbers used as regression input. More importantly, there were a number of experimental control variables that differed between analyses. The spot price and premium series were different from the original ones in several ways. No attempt was made to use the original SPOT variable as had been done before. Instead of regressing SPOT2 on SPOT to obtain a spliced or derived SPOT variable, the discontinued series SPOT was regressed on the still published SPOT2 to obtain a derived series SPOT3. The derived series SPOT4 (obtained as shown in section 1) was a further difference. One key difference was the hedge length in days. In the original study, hedge length varied from 8 to 16 weeks. Here, it varied from 4 to 20 weeks. Two different premia series were used in this study, compared to one in the previous one. Finally, there was no basis of comparison for monthly regressions in the original study. In spite of these differences, results of replication regressions came out reasonably close to the original work as TABLE 1 shows.

TABLE 1: Replication of 1989 Regression Using Two Current Models 1974-1984 Estimation BOLD VALUES DENOTE SIGNIFICANT AT $\alpha=.05$

MODEL	1989 Ward, et. al.	CV fixed across year	CV varies by maturity month
Dependent	PM	PREM2	PREM2
Independent	SPOTCV	CVSPOT2	CV2
Intercept (t)	**1.34980 (10.55)**	**1.59526 (5.414)**	**1.95624 (15.033)**
CV (t)	**-0.15735 (-2.66)**	-0.22061 (-1.915)	**-0.30929 (-5.936)**
CV^2 (t)	**0.02186 (2.4771)**	0.025259 (1.683)	**0.032505 (4.838)**
CV^3 (t)	**-0.00113 (-2.1816)**	-0.001028 (-1.307)	**-0.001333 (-4.025)**
CV^4 (t)	0.00002 (1.9411)	0.000014 (0.980)	**0.000019 (3.530)**
Adjusted R^2	.3437	.3813	.6350
Overall F (p-value)	**8.7233 (.0001)**	**14.115 (.0001)**	**29.268 (.0001)**
Number of Observations	60	60	60
Dependent Variable Mean	1.03901	1.08299	1.08299

Results for Full Period, 1967-1995

One unanticipated problem was that of multicollinearity. Because a polynomial transformation of CVSPOT was made for each of the series (SPOT2, SPOT3, and SPOT4), the members of the independent variable set were closely correlated as TABLE 2 shows.

TABLE 2: Pearson Correlation Among CVSPOT2 Regressors.

	CVSPOT2	$CVSPOT2^2$	$CVSPOT2^3$	$CVSPOT2^4$
CVSPOT2	1.00000			
$CVSPOT2^2$	0.99620	1.00000		
$CVSPOT2^3$	0.98608	0.99678	1.00000	
$CVSPOT2^4$	0.97085	0.98786	0.99711	1.00000

When each equation of estimation was run, results exhibited signs of multicollinearity. Rather than drop individual independent variables, the method of principal components (Chaterjee and Price, 1977) was used for a better specification. Three regression models were run containing the first two principal components for each SPOT series. Coefficients and recovered beta values for each are found on the following pages. Note that CVSPOT2, CVSPOT3, and CVSPOT4 are pure annual averages and so each occurred six times in the regression data set because they were computed across contract maturities. This seems reasonable --- variation in the overall observed spot prices would seem to be logically related to variation in premia. However, the regressions suggest that more work needs to be done to find the appropriate functional form because the statistical significance of the coefficient set varied by choice of roots used. The results are reported for two specifications. First, the originally specified form (Model 1) of Ward, Tuttell and Fairchild:

$$\boldsymbol{PREM} = \beta 0+\beta 1*CVSPOT+\beta 2*CVSPOT^{2}+\beta 3*CVSPOT^{3}+\beta 4*CVSPOT^{4}. \quad (5)$$

Then, a new specification (Model 2) chosen because it maximized the log likelihood function:

$$\boldsymbol{PREM} = \beta 0+\beta 1*CVSPOT+\beta 2*CVSPOT^{1.33}+\beta 3*CVSPOT^{1.66}+\beta 4*CVSPOT^{2}. \quad (6)$$

The second specification (6) was the set of roots found to maximize the log of the likelihood function. Note that in all three cases, the fit as measured by R^2 and the significance of regression coefficients were improved in the new specifications.

Models for Series CVSPOT2

Models 1 and 2 were estimated by the method of principal components. The coefficients are shown below along with Figure 4 which depicts a scatterplot and the regression line given by model 2. There is insufficient statistical evidence in support of the quadric functional form (4) that was used by Ward, Tuttell and Fairchild in the 1989 study. However, model 2's fit is much better, suggesting that at least part of the variation in PREM can be explained by the estimated function of the coefficient of variation of the spot prices (5). Model 2 suggests that around 19% of the variation can be explained by the variability of the spot price. Interestingly, the premium function shows no sign of a plateau as past work has shown. Possible reasons for apparent change in functional form receives more discussion later.

Model 1 for Series CVSPOT2, Principal Components Regression using
$PREM2=\beta_0+\beta_1*CVSPOT2+\beta_2*CVSPOT2^2+\beta_3*CVSPOT2^3+\beta_4*CVSPOT2^4$
(BOLD VALUES DENOTE SIGNIFICANT AT α=.05)

Number of observations: 174					
R-squared = .093778		Adjusted R-squared = .083179			
Variable	Estimated Coefficient	Standard Error	t-statistic		
C	**1.05802**	**.935405E-02**	**113.108**		
P1	-.013163	.938105E-02	-1.40311		
P2	**.037203**	**.938105E-02**	**3.96571**		
Log of likelihood function = 118.699		**F-statistic = 8.84778**			
	β_0	β_1	β_2	β_3	β_4
Value	1.08296	-0.000036135	-0.000032141	-1.49294D-06	-5.04182D-08

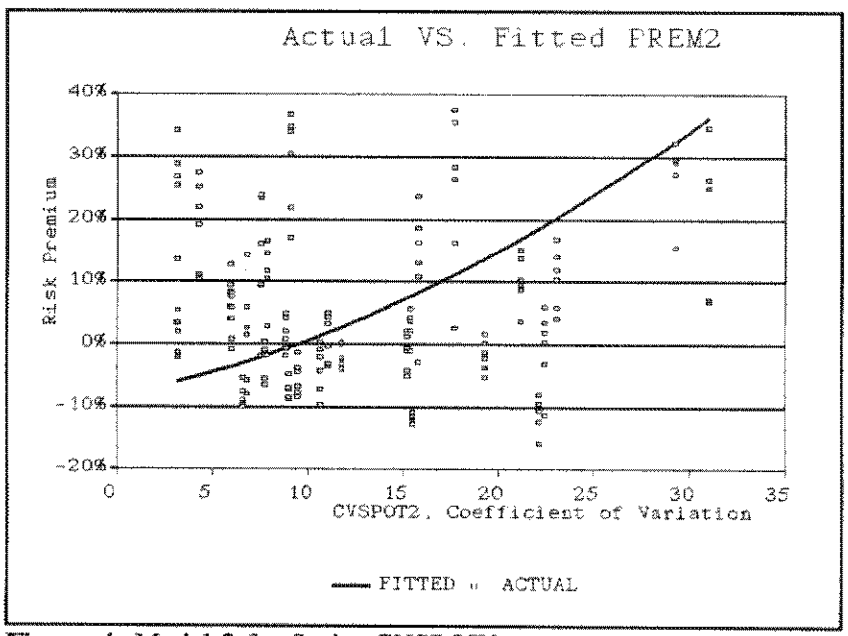

Figure 4, Model 2 for Series CVSPOT2

Model 2 for Series CVSPOT2, Principal Components Regression using
$PREM2 = \beta_0 + \beta_1 * CVSPOT2 + \beta_2 * CVSPOT2^{1.33} + \beta_3 * CVSPOT2^{1.66} + \beta_4 * CVSPOT2^2$
(BOLD VALUES DENOTE SIGNIFICANT AT $\alpha = .05$)

Number of observations: 174					
R-squared = .199492 Adjusted R-squared = .190129					
Variable	Estimated Coefficient	Standard Error	t-statistic		
C	**1.05802**	**.879155E-02**	**120.345**		
P1	**.027866**	**.881692E-02**	**3.16052**		
P2	**-.050361**	**.881692E-02**	**-5.71186**		
Log of likelihood function = 129.490		**F-statistic = 21.3071**			
	β_0	β_1	β_2	β_3	β_4
Value	0.92281	0.0028595	0.0010633	0.00039107	0.00013711

Models for CVSPOT3

As with the case of CVSPOT2, there is insufficient statistical evidence to support the quadric functional form (4). But even though model 1 does not appear plausible, again model 2 explains just under 19% of the variation in premium using the variability of spot price. Figure 5 shows how model 2 fits the CVSPOT3 and PREM3 data. The model suggests that below some threshold coefficient of variation level (around 10) futures prices will not reflect a premium "charged" to hedgers by speculators for transfer of risk. At higher levels of spot price variability, however, a risk premium does occur. Furthermore, the higher the variability, the faster that premium grows. This relationship will be demonstrated in more detail after the third set of models is presented.

Model 1 for Series CVSPOT3, Principal Components Regression using
PREM3=$\beta_0+\beta_1$*CVSPOT3+β_2*CVSPOT3^2+β_3*CVSPOT3^3+β_4*CVSPOT3^4
(BOLD VALUES DENOTE SIGNIFICANT AT α=.05)

Number of observations: 174					
R-squared = .102648		Adjusted R-squared = .092153			
Variable	Estimated Coefficient	Standard Error	t-statistic		
C	**1.05369**	**.819819E-02**	**128.527**		
P1	-.015863	.822185E-02	-1.92941		
P2	**.032721**	**.822185E-02**	**3.97970**		
Log of likelihood function = 141.648		**F-statistic = 9.78034**			
	β_0	β_1	β_2	β_3	β_4
Value	1.08665	-0.00046857	-0.000044396	-1.82606D-06	-5.77221D-08

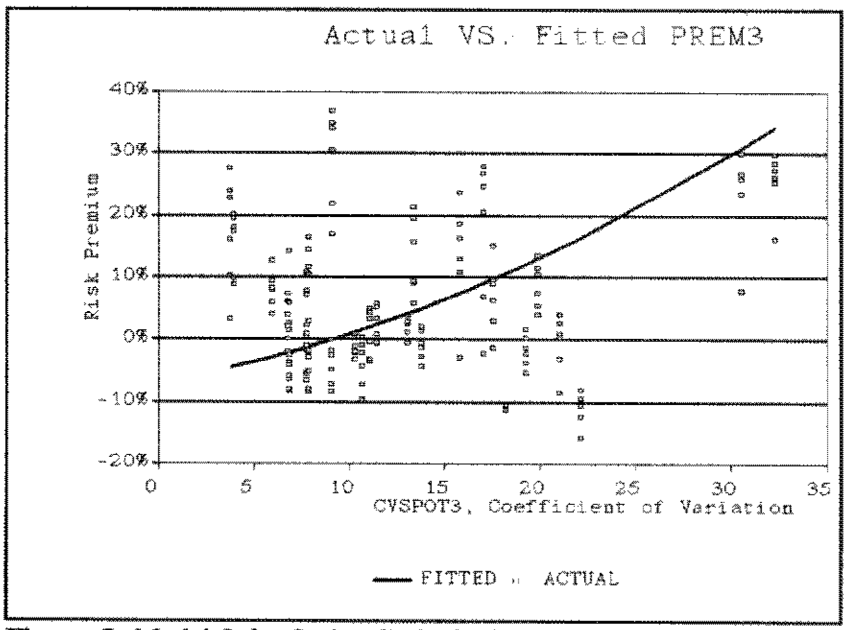

Figure 5, Model 2 for Series CVSPOT3

Model 2 for Series CVSPOT3, Principal Components Regression using
$PREM3 = \beta_0 + \beta_1 * CVSPOT3 + \beta_2 * CVSPOT3^{1.33} + \beta_3 * CVSPOT3^{1.66} + \beta_4 * CVSPOT3^2$
(BOLD VALUES DENOTE SIGNIFICANT AT $\alpha = .05$)

Number of observations: 174					
R-squared = .194375			Adjusted R-squared = .184953		
Variable	Estimated Coefficient	Standard Error	t-statistic		
C	**1.05369**	**.776789E-02**	**135.647**		
P1	**.023868**	**.779031E-02**	**3.06377**		
P2	**-.043980**	**.779031E-02**	**-5.64544**		
Log of likelihood function = 151.030			**F-statistic = 20.6288**		
	β_0	β_1	β_2	β_3	β4
Value	0.93604	0.0025093	0.00092885	0.00033869	0.00011722

Models for CVSPOT4

As with the previous two cases, there is insufficient support for the quadric functional form with the CVSPOT4 data. Note, though, that the differences between models 1 and 2 are more dramatic in this case than in the others. R^2 rises from .026 to .348 from model 1 to model 2, again suggesting that the 1989 results do not fit the newer data. Figure 6 shows the regression equation relating CVSPOT4 to PREM4. Again, note that at levels of CVSPOT4 below approximately 10, no premium is predicted, but at higher levels of price variability, the risk premium increases at an increasing rate.

Model 1 for Series CVSPOT4, Principal Components Regression using
$PREM4=\beta_0+\beta_1*CVSPOT4+\beta_2*CVSPOT4^2+\beta_3*CVSPOT4^3+\beta_4*CVSPOT4^4$
(BOLD VALUES DENOTE SIGNIFICANT AT α=.05)

Number of observations: 174					
R-squared = .025988		Adjusted R-squared = .014596			
Variable	Estimated Coefficient	Standard Error	t-statistic		
C	**1.05152**	**.779356E-02**	**134.922**		
P1	-.407507E-02	.781605E-02	-.521372		
P2	**.016190**	**.781605E-02**	**2.07139**		
Log of likelihood function = 150.456		F-statistic = 2.28123			
	β_0	β_1	β_2	β_3	β_4
Value	1.05867	0.00021811	-0.000012079	-9.09747D-07	-4.10488D-08

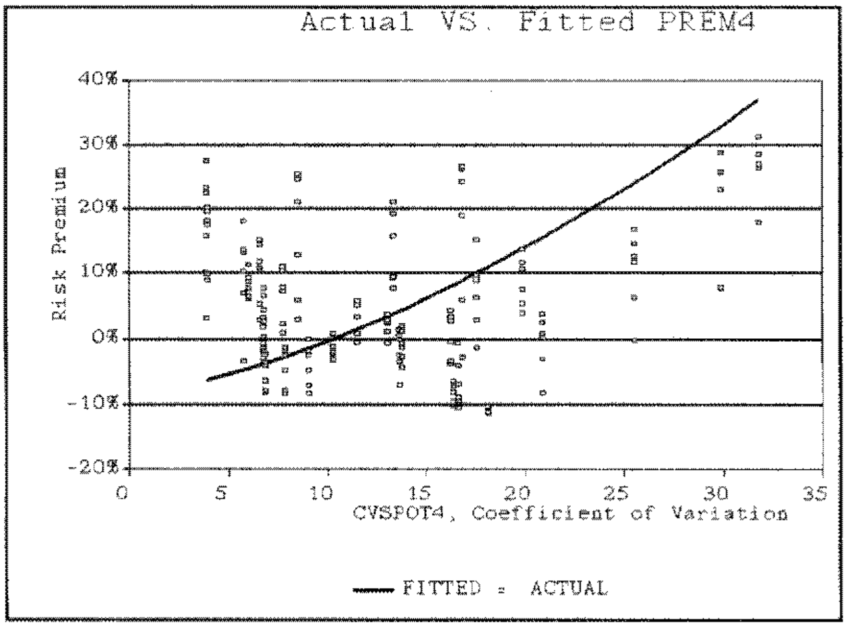

Figure 6, Model 2 for Series CVSPOT4

Model 2 for Series CVSPOT4, Principal Components Regression using
$PREM4 = \beta_0 + \beta_1 * CVSPOT4 + \beta_2 * CVSPOT4^{1.33} + \beta_3 * CVSPOT4^{1.66} + \beta_4 * CVSPOT4^2$
(BOLD VALUES DENOTE SIGNIFICANT AT $\alpha = .05$)

Number of observations: 174					
R-squared = .347759			Adjusted R-squared = .340130		
Variable	Estimated Coefficient	Standard Error	t-statistic		
C	**1.05152**	.637761E-02	**164.878**		
P1	**.027579**	.639601E-02	**4.31194**		
P2	**-.054490**	.639601E-02	**-8.51940**		
Log of likelihood function = 185.343			F-statistic = **45.5865**		
	β_0	β_1	β_2	β_3	β_4
Value	0.91447	0.0027906	0.0010582	0.00039297	0.00013804

Discussion

Two key conclusions can be reached by examination of the regressions reported above. First, the relationship between spot price variability and a risk premium is again confirmed. Secondly, this confirmation appears to be substantially different than that found in the 1989 study suggesting a structural change.

The first conclusion can be summarized aptly using the familiar elasticity measure. If the formula for elasticities is tailored to the variables of analysis then

$$\eta = \frac{dQ}{dP} \frac{\overline{P}}{\overline{Q}}$$
$$\eta = \frac{dPREM}{dCVSPOT} \frac{\overline{PREM}}{\overline{CVSPOT}} . \qquad (7)$$

Using the data, we find that elasticities are: 0.064 for SPOT2, 0.057 for SPOT3, and 0.065 for SPOT4. Thus a 10 percent change in the coefficient of variation is associated with approximately six-tenths of a percent change in the value of PREM.

The second conclusion can be approached by considering a recursive least squares estimation. All this means is that a regression is run each year on data for the preceding periods in the sample and the results are compared. If the relationship being modeled has constant parameters, the results of such recursive regressions demonstrate that the model choice holds well through time. If, on the other hand, regression coefficients exhibit wild swings from year to year or a secular trend, the recursive regression results must be statistically investigated to ascertain whether structural breaks have occurred.

On the next page, a series of graphs of each of the recovered parameters is shown (Figures 7 through 11). For each parameter, note that between 1977 and 1979 there is a sharp change in the values and that all slope parameters (β_1 through β_4) have fallen. Yet during that time, the intercept parameter β_0 has risen steadily. Thus, there is evidence that at low levels of variability (below a CV of 10) there is less of a risk discount than in earlier years. However, with all of the slope parameters falling, it would appear that there is less of a risk premium now than in the past at high levels of price variability.

Two issues remain to be examined with regard to the apparent lack of constancy in the coefficients through time. First, quantification of the degree of statistical significance associated with the differing coefficient values could provide stronger evidence of structural change than just observing a graph. Secondly, if structural change has occurred, the implications for users of the futures markets and the effect of changing parameters on the risk premium given various levels of price variability must be characterized.

A scaled recursive Chow test (Charemza and Deadman pp.71-72, 1993) was used to answer the first issue, whether a statistically significant structural change has occurred. A test statistic was calculated following their method in Figure 12. Note that "for any values above 1 in the graph, the null hypothesis of no structural change between periods t and t-1 would be rejected at the 5% level of significance". In Figure 12, values above 1 suggest a structural change when comparing the following years: 1976-77, 1979-80, 1980-81, 1982-83, 1983-84, 1985-86, 1989-90, 1992-93, and 1993-94. Clearly there have been numerous structural breaks in the relationship between FCOJ spot price variability and risk premia.

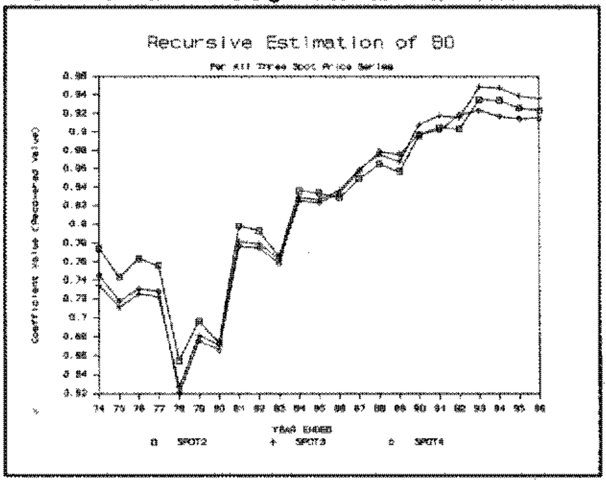

Figure 7, Recursive Estimate of intercept β_0

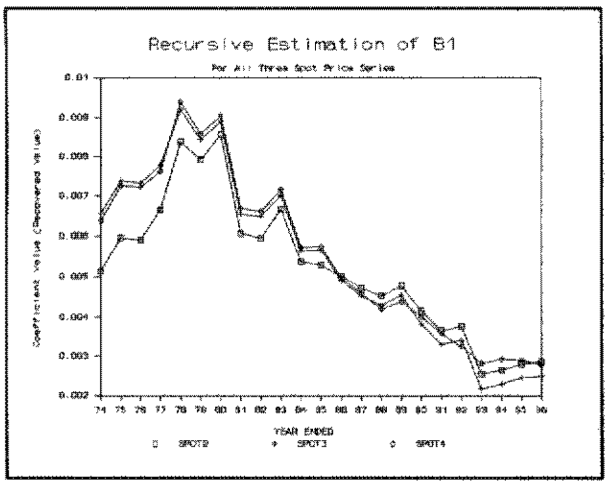

Figure 8, Recursive Estimate of Linear Slope β_1

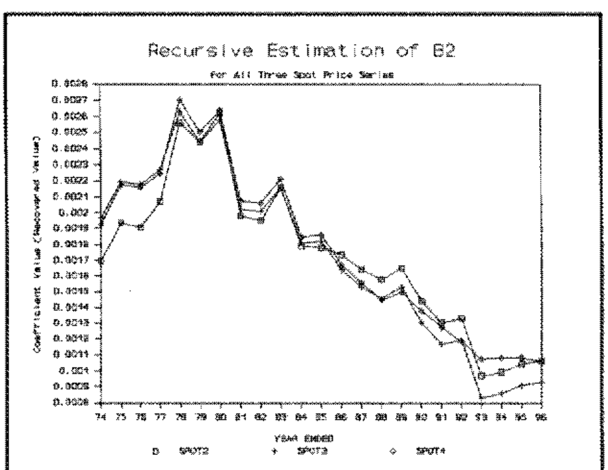

Figure 9, Recursive Estimate of β_2, 4/3 root term

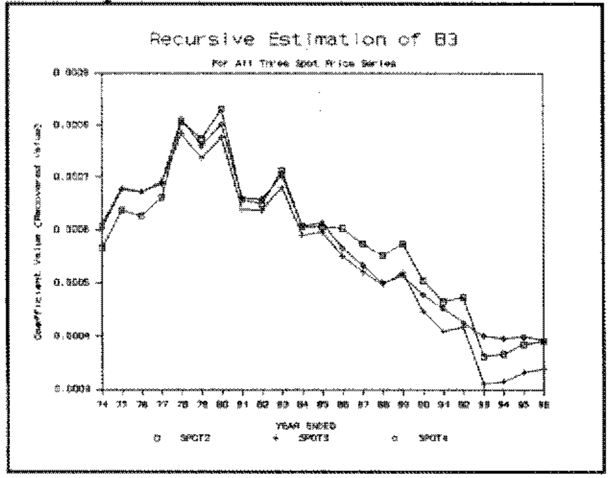

Figure 10, Recursive Estimation 4/3 root slope β_3

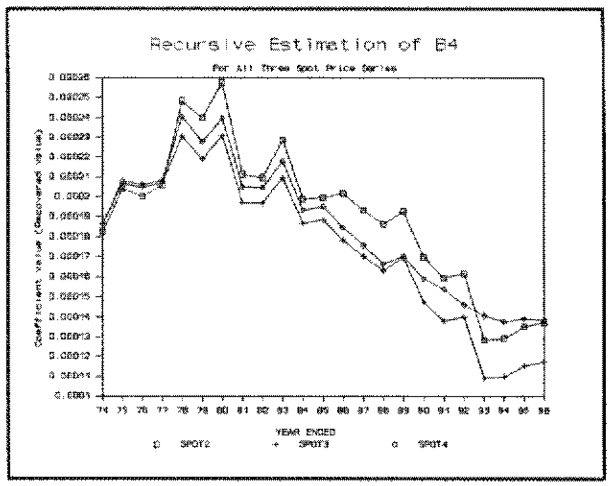

Figure 11, Recursive Estimation β_4, quadratic root

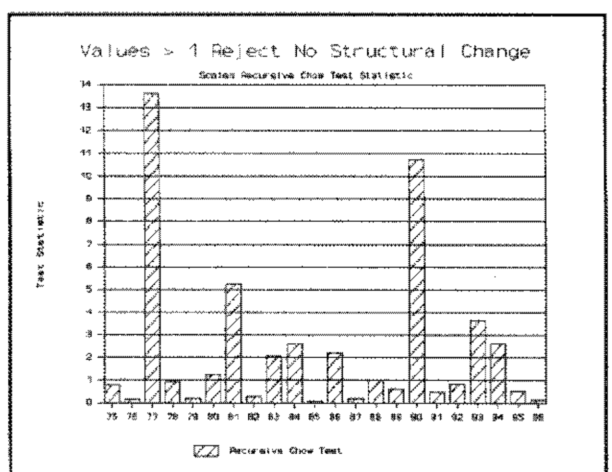

Figure 12, Chow Statistic Test for SPOT2 model

More graphical analysis will help to characterize the meaning of these structural breaks in terms of how price variability affects the risk premium. On the next page, Figures 13 through 18 show the repercussions on risk premia through time from plugging in a particular level of price risk into the recursive regression model for a given year. In these plots, the coefficient of variation of the spot price is held constant through time and the annually estimated regression model estimates for PREM are shown. The three lines represent recursive estimation of models based on the three different spot price series used.

At relatively low levels of price variability (CV below 10) figures 13, 14, and 15 show the overall trend of the estimated relationships is from a fairly significant "risk discount" in the earlier years to a neutral position in the later years. The three graphs on the left side of the page suggest that spot prices are no longer discounted to futures prices at low levels of price risk.

However, the three graphs on the right side of the page tell a different tale. Because all coefficients are positive, the roots in the model guarantee that as CV increases the PREM increases at an increasing rate. At higher levels of risk, a change in parameter value is therefore magnified. At a CV of 15 (Figure 16) the pattern resembles the plots on the left-hand side of the page. (Note that the average CV as measured in the study was approximately 13, in between 10 and 15). At that level of risk there is a trend towards a risk premium (reaching approximately 1.07 in the 1990's) from a neutral point in 1974. Yet at a CV of 20 (Figure 17), there is an initial trend towards more of a premium moving from under 1.15 in 1974 to over 1.19 in the early 1980's and then a trend down again. Finally, at a CV of 30, a peak PREM of over 1.80 in 1980 declines to around 1.35 today.

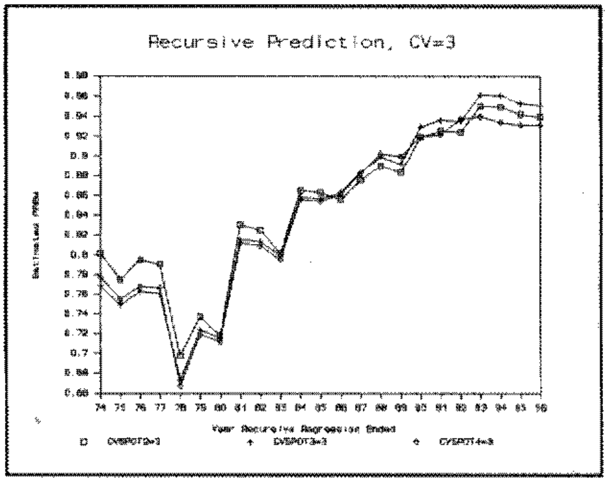

Figure 13, Recursive Prediction, CV=3

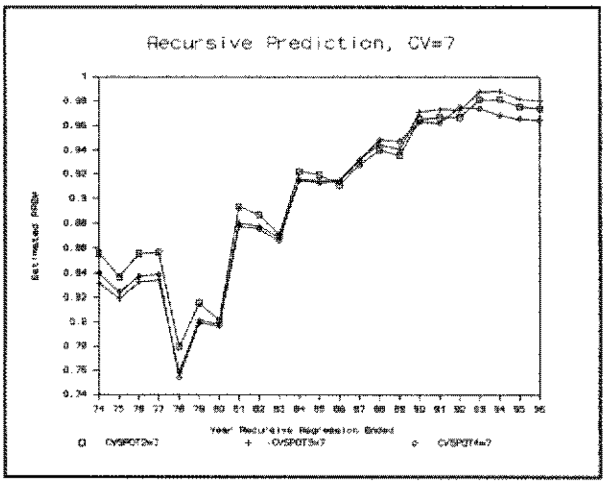

Figure 14, Recursive Prediction, CV=7

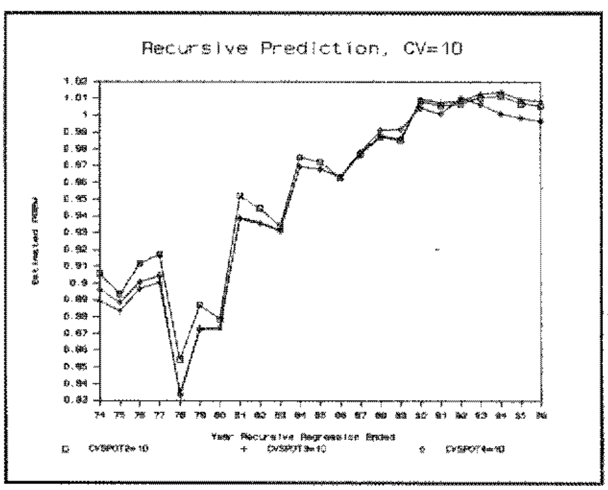

Figure 15, Recursive Prediction, CV=10

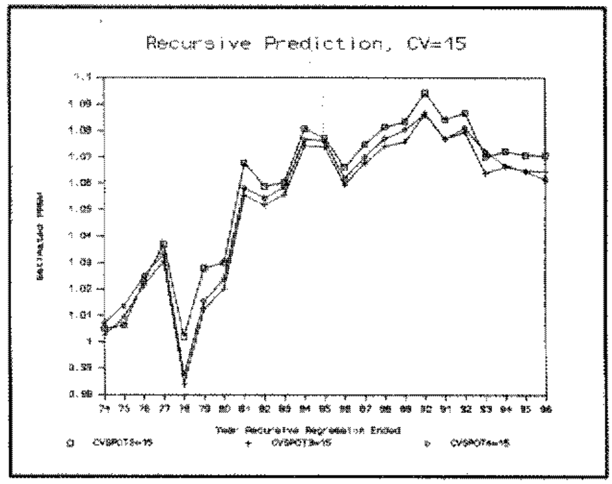

Figure 16, Recursive Prediction CV=15

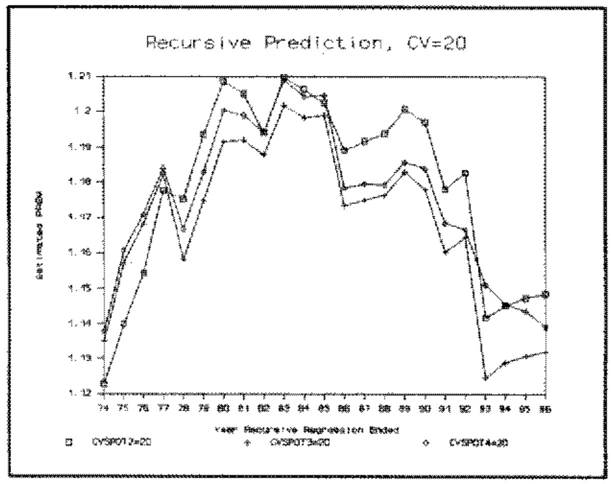

Figure 17, Recursive Prediction CV=20

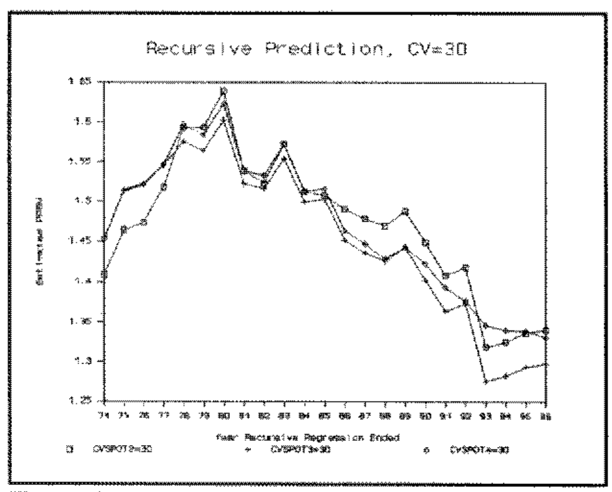

Figure 18, Recursive Prediction CV=30

The results suggest that over time an increasing risk premium has been seen at above average levels of variability, but that at very high levels of variability the premium has actually fallen. The first possible structural change is that over time the futures market has become more efficient at charging for risk based on the probability a given risk level will be experienced. As was noted before, during the sixties and early seventies, the FCOJ contract was often traded rather thinly. Only after speculators and hedgers both became accustomed to FCOJ trading, could enough volume and open interest be built up for the prices to reflect the underlying price risk. Furthermore, it has been only with trading experience that the distribution of price variability has become known to market participants, enabling the pricing mechanism to behave probabilistically.

These results would also be consistent with structural change in the citrus industry itself. Several changes could have possibly lower the premium at one level of price variability while raising it at another. One factor is the emergence of Brazil and other countries as quality and reliable sources of concentrate. Second, additional tank farms have been built over the time period which could contribute to additional holding capacity and change the location basis. Finally, a host of other marketing and culture practices ranging from increased advertising and promotion of orange juice to the migration of Florida groves to freeze-protected areas could be responsible.

Overall, this study confirms the link between price variability and a futures price premium in the FCOJ markets adding additional support to the risk premium theory. However, structural changes in the citrus industry and in FCOJ markets in general appear to have dampened the impact of spot price variability on the risk premium at relatively high levels of variability while increasing the premium at low levels. Additional research is needed to examine how the changing distribution of price variability over time affects risk premia.

REFERENCES

Charemza, Wojciech W.; Deadman, Derek F. ***New Directions in Econometric Practice***. Edward Elgar Publishing, Brookfield, Vermont, 1993.

Chaterjee, Samprit; Price, Bertram. ***Regression Analysis by Example***. Wiley, New York, 1977.

Dasse, Frank A. "Economic Impacts of Frozen Orange Juice Futures Trading on the Florida Orange Juice Industry." Ph.D. dissertation, University of Florida, Food and Resource Economics department, 1975.

Kolb, Robert W. ***Understanding Futures Markets***. Third Edition, Kolb Publishing, Miami, FL.

Malick, William; Ward, Ronald W. "Stock Effects and Seasonality in the FCOJ Futures Basis." ***The Journal of Futures Markets***, 7(1987):157-167.

Tuttell, Maryellen. "Selected Hedging Strategies in the Frozen Concentrated Orange Juice Industry." M.S. Thesis, University of Florida, Food and Resource Economics Department, 1987.

Ward, Ronald W.; Dasse, Frank A. "Empirical Contributions to basis Theory: The Case of Citrus Futures." ***American Journal of Agricultural Economics***, (February 1977:71-80).

Ward, Ronald W.; Niles, James A. "Hedging Strategies in FCOJ Futures." Economic Research Department Report 75-1, Florida Department of Citrus and Food and Resource Economics Department, University of Florida. August 1975.

Ward, Ronald W.; Tuttell, Maryellen; Fairchild, Gary. "Further Evidence of Risk Premiums in the FCOJ Futures Market." Staff Paper 374, December 1989, Food and Resource Economics Department, University of Florida.

Working, Holbrook. "Theory of the Inverse Carrying Charge in Futures Markets." ***Journal of Farm Economics***, (1948:1-28).