Measurement of Price Risk in Revenue Insurance: Implications of Distributional Assumptions*

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May 14, 1998

Abstract

A variety of crop revenue insurance programs have recently been introduced. A critical component of constructing revenue insurance contracts is a measure of the risk associated with stochastic prices. This paper evaluates distributional implications of alternative methods for estimating price risk and deriving insurance premium rates. We utilize a variety of specification tests to evaluate distributional assumptions. Discrete mixtures of normals provide flexible parametric specifications capable of recognizing the skewness and kurtosis present in commodity prices. Conditional heteroscedasticity models are used to evaluate determinants of futures price variability.

*Paper to be presented at the 1998 AAEA Summer Meetings in Salt Lake City. This research was supported by the Economic Research Service of the USDA. The views expressed herein are those of the authors and not necessarily those of the Economic Research Service or the U.S. Department of Agriculture. Roberts and Goodwin are at North Carolina State University. Coble is at Mississippi State University. Direct correspondence to Goodwin at P.O. Box 8109, Raleigh, NC 27695, (919) 515-4547, E-mail: barry_goodwin@ncsu.edu

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1 Introduction

A variety of crop revenue insurance programs have recently been developed to supplement the standard multiple peril crop insurance that has existed in the U.S. since the 1930s. In general, these programs guarantee producer revenues by protecting against any revenue-diminishing combination of low prices and/or low crop yields. The revenue insurance contracts guarantee producers a minimum level of revenues. If, because of any combination of poor yields or low prices, revenues are beneath the guaranteed level, insured farmers receive an indemnity payment equal to the difference between realized and guaranteed revenues.

Three alternative crop revenue insurance products currently exist: crop revenue coverage (CRC), income protection (IP), and revenue assurance (RA).[1] Conventional crop insurance programs have been hampered by actuarial problems that have led to significant losses. In particular, program outlays exceeded $8.9 billion between 1990 and 1997 (US-GAO (1998)). These high losses have been attributed to adverse selection and moral hazard issues. Inaccurate premium rates and performance monitoring problems underlie the actuarial shortcomings of crop insurance programs. In the case of revenue insurance, a critical component of the proper insurance premium is a rate that accurately reflects the price dimension of risk. A variety of methods for measuring price risk have been proposed. A report recently released by the General Accounting Office (US-GAO (1998)) is critical of the actuarial methods underlying all three revenue insurance plans.

An advisory meeting intended to provide recommendations to the Federal Crop Insurance Corporation on proper actuarial methods for rating revenue insurance contracts was held in June 1996. Considerable disagreement existed among participants regarding the proper approach for rating price risk. Three alternative approaches to rating price risk were discussed. The current CRC program uses a historical series (1973-1996) of futures prices, quoted at planting time (F_t) and harvest time (P_t) to derive a "forecast error" $e_t = P_t - F_t$, that is then assumed to be normally distributed. The portion of premium associated with price risk is then calculated using standard results for a

[1] Although the issues discussed in this paper are pertinent to all three products, the specific provisions of the contract and examples are taken from CRC.

normal distribution. An alternative approach which utilized proportional errors (e_t/P_t) under the assumption of normality was recommended as an alternative to existing procedures. This approach assumes that errors are proportionally larger as prices are higher and is thus analogous to assuming a log-normal distribution for prices. A third approach to rating price risk would utilize existing options markets to derive market-based measures of price risk (volatility). This approach, while clearly preferable, is not appropriate for all revenue insurance contracts since the necessary options contracts do not exist for all crops currently insured.

The assumption of log-normality would seem to have considerable precedent in the financial literature. Models of price variability and options price determination have typically assumed that prices are log-normally distributed. In particular, the Black-Scholes (1973) option valuation formula, which is based upon the assumption of log-normally distributed prices, has realized widespread application and acceptance. In spite of this prominence, however, relatively little attention has been given to evaluating the extent to which prices adhere to distributional assumptions and the potential implications of distributional misspecification. More recent research (see, for example, Cornew, Town, and Crowson (1984); Hudson, Leuthold, and Sarassoro (1987); and Hsieh (1989)) has documented leptokurtosis, skewness, and other distributional characteristics inconsistent with normality and log-normality. Recognition of these points has led to the development of a variety of approaches to easing distributional restrictions and providing modeling techniques that allow for non-normal distributions.

It is often argued that the distribution of market prices may be sensitive to market conditions and thus that distributional shifts may occur if market conditions change. In such a case, the price series may display unusual distributional characteristics such as skewness, kurtosis, and multiple modes. Recent research has applied alternative empirical techniques to derive price distributions that accurately reflect characteristics that are not consistent with normality. In one line of research, discrete mixtures of known distributions are used to represent distributional characteristics that are not compatible with normality. This approach is often motivated by the assumption that, although a standard distribution is appropriate under a given set of market conditions, different underlying market conditions may result in different distributions. Thus, when the entire series of prices are observed, the underlying process is a mixture of the standard distributions. In other research, mixed-jump processes have been used to represent nonstandard distributions. Jump processes are appropriate in situations where random shocks shift the entire distribution. In both cases, the resulting distributions are capable of representing characteristics of a series that may not be consistent with normality or log-normality. For example, a simple mixture of two normals is capable of representing a standard, symmetric normal distribution as well as nonsymmetric distributions, skewness, bimodality, and leptokurtosis.

The objective of this analysis is to explore distributional properties and characteristics associated with corn and wheat prices. The specific focus of the analysis is to evaluate the measurement of price risk for the purposes of premium rate determination for crop revenue insurance programs. The paper proceeds according to the following plan. The next section describes revenue insurance products available in the U.S. Econometric methods applied to the analysis of price risk are then developed. The fourth section presents models of conditional corn and wheat price distributions using standard ordinary least squares techniques as well as maximum likelihood estimates of discrete mixtures of normals. The fourth section also presents conditional heteroscedasticity models that relate price variation to a number of explanatory factors. The final section of the paper contains a brief review of the analysis and offers some concluding remarks.

2 Revenue Insurance Programs

Standard multiple peril crop insurance (MPCI) has been in existence in various forms since the 1930s. This insurance pays indemnities at a predetermined price whenever realized yields are less than actual yields. A shortcoming of standard MPCI exists in the price (determined prior to planting season) at which indemnities are paid. When yield losses are widespread, market prices are likely to be higher. Farmers receiving indemnities for lost yields may actually be reimbursed somewhat less (in bushel terms) than their guarantee since their indemnities likely reflect a price that is lower than the market. Revenue insurance had its beginnings with an optional rider that paid indemnities at harvest-time market prices. In conjunction with an put option contract, this allowed producers to guarantee a minimum level of crop revenues. This coverage was extended to form the basis for individual crop revenue coverage (CRC). CRC is currently available in major growing regions for corn, soybeans, wheat, cotton, and grain sorghum. CRC has been quite successful, accounting for over 26% of corn crop insurance sales in 1997.

Income protection (IP) was developed at Montana State University under a directive of the Federal Crop Insurance Act to create a pilot cost of production plan. IP insurance is available for corn, soybeans, grain sorghum, cotton and wheat in major growing regions. IP guarantees a minimum level of crop revenues, based upon forecast prices, individual farm yields, and area yields. If realized revenues fall beneath the revenue guarantee, producers receive an indemnity payment for the amount of the shortfall.

Revenue Assurance (RA) was developed by the Iowa Farm Bureau as a pilot program for corn and soybeans in Iowa. RA provides the option for "whole-farm" insurance in that producers insuring both corn and soybeans receive significant premium discounts. RA provides a guaranteed minimum level of revenue which is determined by individual farm yields and futures prices (adjusted for the local historical basis). If realized revenues are beneath the guarantee because of either low prices, low yields, or both, farmers receive an indemnity payment for the amount of the shortfall. A unique characteristic of the RA program is the utilization of market-based measures of price risks that are available in options markets. In contrast, the CRC and IP programs utilize historical futures prices to develop measures of price risks. RA actuarial procedures utilize estimates of a beta distribution to model yield risks.

3 Econometric Methods

Revenue insurance contracts require a forecast of harvest time prices, made conditional on information available at planting time. In addition, a measure of the uncertainty associated with the price forecast is needed to construct a premium rate reflecting the risk of adverse movements in prices. In all three cases, futures prices are utilized to construct forecasts of harvest-time prices. In the case of RA, options markets are used to gauge the uncertainty associated with prices. IP and CRC instead utilize historical price movements to evaluate price risks. The measurement of price risks in both the RA and CRC programs is heavily dependent upon assumptions regarding the parametric distributions underlying price movements. RA utilizes standard Black-Scholes (1973) results to construct implied volatilities from observed options prices. As noted above, such an approach assumes log-normally distributed prices. In contrast, CRC assumes normally distributed prices in the construction of the price component of the revenue insurance premium. IP utilizes a nonparametric "empirical distribution" approach.[2]

This analysis utilizes two distinct approaches for evaluating price risk. In the first, a set of annual price data is utilized to estimate price distributions and to evaluate insurance premia under alternative distributional assumptions. The second utilizes maximum likelihood estimates of conditional heteroscedasticity models to evaluate exogenous determinants of price variability.

Discrete mixture distributions represent a flexible, parametric approach to modeling probability distribution functions whose intrinsic characteristics are largely unknown. A k-component mixture density function is given by:

$$f(x) = \sum_{i=1}^{k} [\lambda_i f_i(x)], \tag{1}$$

where the probability weights, λ_i satisfy the conditons that $\sum_{i=1}^{k} \lambda_i = 1$ and $\lambda_i > 0$ for all i. Various densities are commonly applied in representing the underlying components of the mixture. The most common approach involves utilizing normal densities:

$$f_i(x) = \frac{1}{\sqrt{2\pi\sigma_i^2}} e^{\frac{(x-\mu_i)^2}{-2\sigma_i^2}}. \tag{2}$$

Mixtures of normals nest a conventional normal distribution (obtained when $\mu_1 = \mu_2 = \ldots = \mu_k$ and $\sigma_1 = \sigma_2 = \ldots = \sigma_k$. Asymmetric and bimodal distributions may result when the $\mu_i's$ are not all equal. Kurtosis is implied when the $\sigma_i's$ are not all identical.

Standard maximum likelihood estimation techniques are commonly used to estimate mixture distributions. There are, however, particular characteristics of mixture problems that may complicate estimation. Nonlinear estimation techniques may have a tendency to concentrate component densities on individual points. In such a case, the σ_i associated with that point goes to zero and the likelihood function becomes numerically unstable. To prevent such instabilities, the λ_i and σ_i terms may be constrained to be positive. The random variable x may also represent a conditional mean in a manner analogous to the standard linear regression problem. In this case, x may be replaced by $y - X\beta$ and the parameters of the conditional mean equation β may be estimated jointly with the parameters of the probability distribution σ_i, μ_i, and λ_i.

[2]Nonparametric density estimation techniques offer complete flexibility in representing characteristics of a distribution. Such flexibility does not, however, come without a significant loss in efficiency. Thus, the nonparametric techniques may not be appropriate for the small samples which are commonly available for measuring price risk. In that pdf functions are commonly used as kernel functions in nonparametric density estimation, the nonparametric techniques are analogous to mixtures of a large number of components.

A second component of our evaluation of price risk utilizes parametric maximum likelihood estimates of a conditional heteroscedasticity model. We assume that the variance of conditional prices (i.e., price differences) is proportional to a function of several exogenous factors which we hypothesize to be related to price variability. In particular, we assume that the variance of prices for an individual contract i quoted at time t are given by:

$$\sigma_{it}^2 = \sigma^2 f(Z_{it}\gamma). \tag{3}$$

We assume that the conditional variance function $f(Z_{it}\gamma)$ is a quadratic version of a linear index (i.e., $(Z_{it}\gamma)^2$). This ensures nonnegative variances for all observations. Under the assumption of normality, the following log-likelihood function is maximized in order to obtain estimates of γ and, if applicable, of parameters of a conditional mean equation β:

$$lnL = -\frac{n}{2}[ln(2\pi) + ln\sigma^2] - \frac{1}{2}\sum_{i=1}^{n} ln((Z_{it}\gamma)^2) - \frac{1}{2\sigma^2}\sum_{i=1}^{n}\frac{(y_i - \mu_i)^2}{(Z_{it}\gamma)^2}. \tag{4}$$

4 Empirical Application

The empirical analysis consists of two components. The first utilizes a long series of annual observations on planting and harvest time futures prices. In particular, corn and wheat futures were collected from selected issues of the Chicago Board of Trade's *Yearbooks* for the period covering 1899 to 1960. Data for subsequent years were taken from the Bridge financial database. Monthly observations for contracts expiring at harvest (September for corn and July for wheat) were constructed by taking the midpoint of the monthly high and low price quotes at planting times (January for corn and December for wheat).[3] The "harvest-time" price for each contract was that quoted in the month preceding the contracts' expiration. A second segment of the analysis utilized the Bridge database of daily settlement prices to construct monthly average futures prices for all contracts in all months. Expiration prices were the average in the month preceding the contract's expiration.[4]

Ordinary least squares and standard nonlinear estimation techniques were utilized to estimate alternative models of price differentials. In the first segment of the analysis, a price relationship

[3] This approach was necessitated by the available data— daily prices were not available before 1959. An evaluation of the difference in the monthly price constructed in this manner and a monthly average of daily closing prices revealed no significant difference. In particular, the average differential between the alternative monthly prices was nearly zero.

[4] This approach is analogous to the treatment of futures prices in constructing CRC premium rates.

of the form $P_t = \alpha + \beta F_t$ was estimated, where P_t represents the harvest-time price and F_t is the planting-time futures price. An "efficient-markets" relationship would imply that futures prices are unbiased forecasts of expiration-time prices and thus that $\alpha = 0$, $\beta = 1$. Restricted versions of the price models imposed these restrictions and thus considered relationships among price differentials.

Table 1 presents estimates for the unrestricted and restricted models of futures price relationships for corn and wheat. The models are each estimated in three different ways– ordinary least squares (OLS), OLS applied to logarithmic prices, and via maximum likelihood techniques applied to a two-component mixture of normals. In restricted versions of the OLS and logarithmic OLS models, the approach is analogous to assuming normality and log-normality for the price differentials (i.e., to the extent that normality is used to construct insurance premium rates from the residuals). The restricted mixture case assumes that the price differential is distributed according to the mixture and the parameters of the mixture are thus estimated via maximum likelihood.

Bera-Jarque (1980) conditional moment tests of normality are used to assess the extent to which the OLS residuals and price differentials are consistent with normality and log-normality. The tests overwhelmingly reject normality and log-normality for both corn and wheat. Such a result makes the assumptions of normality and log-normality which are used to motivate the construction of revenue insurance premia questionable and suggests that alternative, flexible distributional specifications may be preferred. The OLS estimates for the level and logarithmic models have price coefficients which are slightly less than one. The mixture model for corn has a price coefficient of .81, which is somewhat far from one and thus may be questionable. The price coefficient for the wheat mixtures model is very similar to estimates for the other models.

Prices were forecast for the last observation (1997) and insurance rates were based upon a guarantee of 100% of this forecasted level.[5] The restricted models guaranteed 100% of the price quoted at planting time. As would be expected, rates based upon log-normality are considerably higher than those based upon normality. This reflects the positive skewness inherent in the log-normal distribution. In contrast, rates for the mixture of normals cases are somewhat lower than those generated by normality or log-normality. This is particularly true in the case of corn. This lower rate, however, reflects the lower forecasted price, which implies a much lower price guarantee.

[5]An insurance premium rate is given by expected loss over total liability. Expected loss is given by the product of the probability of a loss and the expected price given that a loss occurs. Numerical integration was utilized to estimate these probabilities and expected loss levels.

The mixture of normals case generates wheat premium rates that are quite similar to those for the normality case.

Differences in the premium rates and underlying distributions are revealed in plots of the densities implied by OLS and the mixture of normals cases. Figure 1 illustrates nonparametric kernel estimates of the densities associated with the OLS residuals and the parametric mixture of normals cases.[6] Strong positive skewness is revealed in the estimates. In several cases, slight bimodality is revealed, suggesting that large, positive errors are sometimes observed. The distributions do not resemble normal densities and thus the assumption of normality would again seem questionable.

In all, this segment of the analysis suggests that current premium rates may be higher than the underlying price risk would suggest. Rates calculated in this manner are, however, based solely upon historical information and thus may not reflect the uncertainty underlying market participants' actions at the time contracts are offered.

A second segment of the analysis evaluates exogenous determinants of price variation. Restricted versions of the models (i.e., for price differentials) are used. Thus, models relating the variance of the expected expiration price, conditional on prices quoted prior to contract expiration, are estimated using maximum likelihood methods.[7] In that the pooled data set consists of many overlapping contracts, a complex form of moving-average error correlation is inherent in the price differentials. To allow for such correlation, we specify a first-order autoregressive correlation process among the monthly prices.[8] Maximum likelihood estimates and summary statistics are presented in Table 2. The default is a January contract quoted in the previous January. The estimates reveal that increased months to maturity decreases price volatility. This result is consistent with the "Samuelson Hypothesis" (Samuelson (1976)) which maintains that prices will reflect more information and thus be more volatile as contract expiration nears.[9] The results reflect significant differences in price variability across alternative contracts. Contracts which expire in the months immediately preceding harvest (July for corn and May for wheat) appear to have the most volatile

[6]Note that the nonparametric densities do not assume normality. OLS is a nonparametric estimation technique providing unbiased parameter estimates regardless of the underlying distribution. It has been noted, however, that least-squares estimation may make sample residuals more symmetric than the actual errors (see Huang and Bolch (1974).

[7]Note that the models assume that the conditional errors are normally distributed with a conditional variance that depends upon a number of explanatory factors.

[8]The correlation structure is restricted to prevent correlation corrections across alternative contracts.

[9]Recent results presented by Hennessy and Wahl (1996) were not consistent with the Samuelson hypothesis.

prices. Significant differences in the variability of prices over the growing season are also revealed in the estimates. Corn prices appear to be the most variable in June and July, the most critical growing period. Likewise, wheat prices appear to be the most variable in April. Wheat prices also appear to be quite variable in June, perhaps reflecting harvest realizations or growing conditions for substitute spring wheats.

In all, the results show that futures price variability may be conditioned upon a number of explanatory factors, including months to maturity, month of contract, and month of price quote. These results may offer benefits for constructing premium rates for the price-risk component of revenue insurance contracts. The modeling approach allows a much larger sample to be utilized in constructing premium rates, potentially improving inferences. Price uncertainty can be conditioned upon the months of the contract and price quote used in constructing revenue insurance contracts.

5 Concluding Remarks

This analysis evaluates distributional implications of modeling price uncertainty. The issue of price uncertainty has taken on increased importance with the introduction of three revenue insurance programs. In addition, changes in the farm policy environment that occurred with the 1996 Farm Bill have led to increased concerns regarding the stability of farm prices.

The results indicate that conventional approaches to measuring price variability and rating revenue insurance may be misspecified. Our empirical results strongly reject both normality and log-normality. Flexible distributional specifications based upon discrete mixtures of normals reveal a slight tendency for bimodality and strong positive skewness. Insurance premium rates based upon the mixture of normals case (which effectively nests normality and log-normality) are slightly smaller than those implied by normality and significantly smaller than those implied by log-normality. An analysis of the conditional variance of corn and wheat prices reveals that variance decreases as time to maturity rises and is highest during important growing periods.

Future research will consider additional explanatory factors (such as options premia, stocks, demand shocks, and growing conditions) which may be used to condition variance forecasts. Additional attention will also be given to modeling the complex correlation structure underlying our analysis of overlapping contracts.

Table 1. Maximum Likelihood Parameter Estimates and Summary Statistics

Parameter	OLS	Log-Normal OLS	Mixture	Restricted Mixture
		Corn		
α	13.8443	0.4676		
	(7.1627)*[a]	(0.1693)*		
β	0.9120	0.9063	0.8087	
	(0.0438)*	(0.0353)*	(0.0293)*	
λ			0.8928	0.5958
			(.0522)*	(0.0888)*
μ_1			18.6397	0.3371
			(4.2833)*	(2.1784)
σ_1			18.5889	10.8401
			(1.8038)*	(1.7450)*
μ_2			108.7290	3.2680
			(27.6845)*	(9.8612)
σ_2			38.9203	53.4498
			(18.2851)*	(7.6627)*
$\hat{P}$	239.4381	240.7328	228.5558	247.3750
$Pr\{P < \hat{P}\}$	0.5015	0.4962	0.6246	0.5212
Rate	5.6702	7.3446	5.1426	4.5163
Bera-Jarque Test	13698.38	1156.53		
		Wheat		
α	11.5468	0.2652		
	(6.5464)	(0.1297)*		
β	0.9371	0.9486	0.9344	
	(0.0296)*	(0.0253)*	(.0263)*	
λ			0.7464	0.3337
			(.0860)*	(0.0951)*
μ_1			7.8977	−0.9985
			(4.1681)*	(7.8967)
σ_1			14.1964	52.3440
			(1.8793)*	(8.5388)*
μ_2			24.3102	−0.3426
			(14.9832)	(1.9365)
σ_2			54.9053	12.1927
			(10.2585)*	(2.1578)*
$\hat{P}$	330.4983	331.9241	330.2235	340.3750
$Pr\{P < \hat{P}\}$	0.4934	0.4962	0.5553	0.4971
Rate	3.7265	4.9878	2.9860	2.9216
Bera-Jarque Test	7895.48	1658.61		

[a]Numbers in parentheses are standard errors. Asterisks indicate statistical significance at the $\alpha = .05$ or smaller level.

Table 2. Maximum Likelihood Parameter Estimates and Summary Statistics

for Conditional Price Heteroscedasticity Models

Variable	Corn	Wheat
ρ	0.9476	0.9061
	(0.0028)*[a]	(0.0045)*
σ^2	8.35629	16.9135
	(0.3616)*	(0.7325)*
Months to Maturity	−.0220	−0.0105
	(0.0020)*	(0.0028)*
March Contract	0.0336	−0.0160
	(0.0292)	(0.0316)
May Contract	0.0352	0.0044
	(0.0313)	(0.0315)
July Contract	0.1061	−0.0594
	(0.0332)*	(0.0297)*
September Contract	0.0030	−0.0286
	(0.0294)	(0.0311)
February Quote	0.0242	−0.1609
	(0.0408)	(0.0399)*
March Quote	−0.0697	−0.0864
	(0.0400)	(0.0497)
April Quote	0.2950	0.3775
	(0.0508)*	(0.0561)*
May Quote	0.1683	−0.0733
	(0.0571)*	(0.0454)
June Quote	0.8301	0.2589
	(0.0687)*	(0.0576)*
July Quote	1.2130	−0.0967
	(0.1060)*	(0.0496)
September Quote	0.0918	0.5949
	(0.0470)*	(0.0610)*
October Quote	0.1971	−0.0445
	(0.0470)*	(0.0422)
November Quote	0.1117	0.1308
	(0.0470)*	(0.0477)*
December Quote	0.0820	−0.1842
	(0.0447)	(0.0386)*
R^2	0.9441	0.9103
n	2575	2080

[a]Numbers in parentheses are standard errors. Asterisks indicate statistical significance at the $\alpha = .05$ or smaller level.

Figure 1.A. Corn Price Density: OLS Residuals

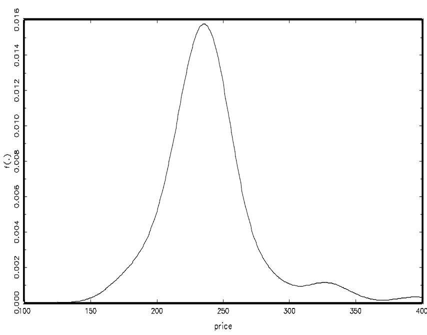

Figure 1.B. Wheat Price Density: OLS Residuals

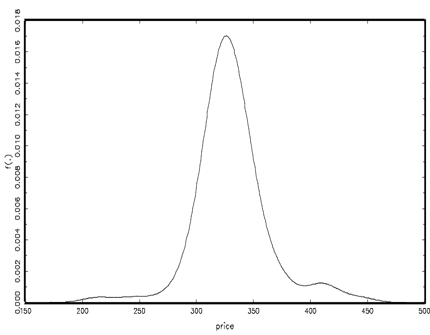

Figure 1.C. Corn Price Density: Unrestricted Mixture

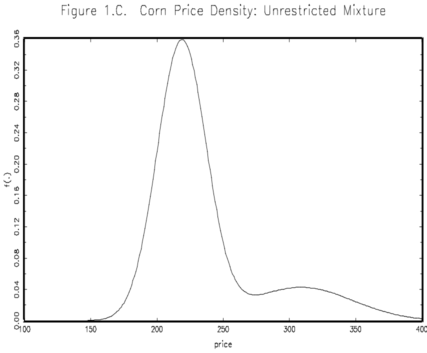

Figure 1.D. Wheat Price Density: Unrestricted Mixture

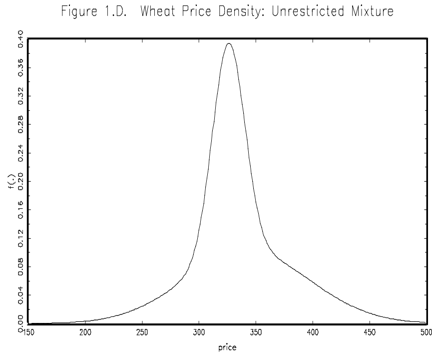

Figure 1.E. Corn Price Density: Price Differences

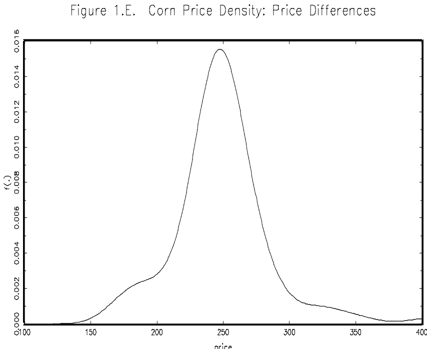

Figure 1.F. Wheat Price Density: Price Differences

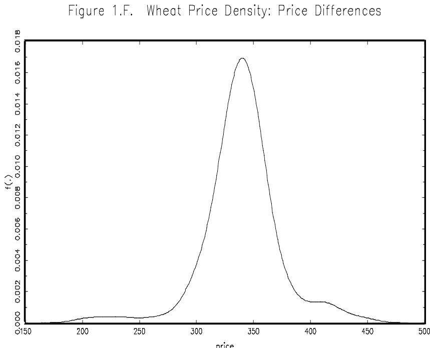

Figure 1.G. Corn Price Density: Restricted Mixture

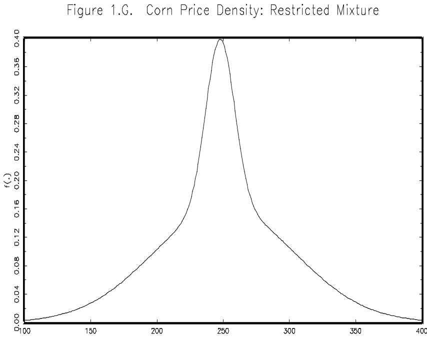

Figure 1.H. Wheat Price Density: Restricted Mixture

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