

**Price Risk in Supply Equations: An Application of
GARCH Time-Series Models to the U.S. Broiler Market**

by

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I. Introduction

In recent years, agricultural economists have sought to develop and refine the theoretical and conceptual tools necessary for evaluating the effects of risk on agricultural markets. Regarding the conceptual analysis of risk, much work has focused on extending neoclassical theories of the firm to include price and/or output risk (Pope and Kramer; Chavas and Pope; Chavas and Pope, and Leathers; Myers). With respect to the empirical investigation of risk, there is growing evidence that risk variables are important in econometric models of agricultural supply. For instance, Behrman and Just found that price and revenue risk variables were important conditioning variables in econometric supply models for Thailand and California, respectively.

While headway has been made, it follows that more work remains to be done. An important question in empirical work is how the process used to generate proxy variables for unobservable expectations of price and price risk should be specified and estimated. The most common measure of price risk used in econometric studies is a weighted moving average of the squared deviations between lagged expected and realized prices (revenues). For example, Just generalized the adaptive expectations framework, popularized in agricultural supply analysis by Nerlove, to include risk terms. Although the resulting model is highly nonlinear, Just shows that a conditional least squares procedure can be used to estimate the parameters. Related methods for modeling risk have been proposed and applied by Traill, Ryan, Winter and Whittaker, Brorsen, Chavas, and Grant, and others.

More recently, attempts have been made to use time-series models to generate instruments for expected price and risk variables in supply equations (e.g., Antonovitz and Roe; Antonovitz and Green). Problems arise, however, when standard time-series models are used to construct risk variables because both the conditional and unconditional variances associated with such models are time invariant (Engle). The result is that *ad hoc* procedures must be used to obtain time-varying estimates of risk variables for use in econometric supply analysis.^{1/} While the use of time-series models to generate expectations variables in econometric models has appeal (see, e.g., Wallis, Feige and Pearce for a detailed discussion), it follows that different procedures are required before such models can be used to successfully generate risk variables.

Fortunately, methods are now available which extend the optimal forecasting properties of time-series models to include variance terms as well. Specifically, generalized autoregressive conditional heteroskedastic (GARCH) time-series models, as originally proposed by Bollerslev, can be used to estimate conditional price and variance expectations in econometric supply models. The unique feature of GARCH processes relative to standard time-series models is that the conditional variance, h_t , associated with a random variable y_t is allowed to vary over time. In particular, the conditional variance is specified as a function of past innovations, ϵ_t , from an

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autoregressive (AR) model used to explain y_t , as well as lagged values of h_t .

Given the above, the objective of this paper is to explore the use of GARCH models to generate conditional expectations for both the mean and variance of price in agricultural supply equations. Specifically, we estimate a risk-responsive supply equation for the U.S. broiler industry using expected price and risk variables generated by a GARCH process. In developing the estimation framework, we show that a price equation with a GARCH error process can be estimated simultaneously with a structural supply model. The resulting model is closely related to the multivariate GARCH models considered by Engle and Bollerslev and is also similar to the rational expectations models considered by Wallis.

The broiler market seems reasonable to investigate for several reasons. First, previous research has found that price risk is an important variable in broiler production (Aradhyula and Holt, 1989). Also, production risks are relatively small in this industry, but short-term price fluctuations can be substantial. Finally, previous research has also found that GARCH processes can be successfully used to model retail broiler prices (Aradhyula and Holt, 1988).

The remainder of the paper is organized as follows. In the next section, several aspects of modeling expectations using GARCH processes are reviewed. Next, the GARCH framework is used to estimate an econometric model of broiler price and production. The resulting supply model is then compared with estimates of a risk-responsive supply equation obtained using Just's adaptive expectations framework. The final section examines the potential for using GARCH models to estimate risk-responsive supply equations and reviews implications for future research.

II. GARCH Models, Expectations, and Risk

This section reviews methods of incorporating risk into supply equations. Specifically, we focus on the use of GARCH processes for modeling risk response.

GARCH Processes

The GARCH(p,q) process associated with a price series can be obtained by letting ϵ_t be an innovation in a linear regression

$$\epsilon_t = P_t - \beta(L)P_{t-1} \quad (1)$$

where P_t is current price (the dependent variable) and $\beta(L)$ is a polynomial lag operator in L containing the unknown parameters (b_0, \dots, b_n) to be estimated. Here ϵ_t denotes a discrete-time real valued stochastic process with a normal conditional distribution given by

$$\epsilon_t | \Omega_{t-1} \sim N(0, h_t) \quad (2)$$

where h_t is the conditional variance of ϵ_t and Ω_{t-1} is the information set available at time $t-1$. Among other things, the information set Ω_t would include, but is not limited to, past realizations of P_t . Given the

information set Ω_{t-1} , the conditional expectation of P_t for period t , viewed in period $t-1$, is simply

$$P_t | \Omega_{t-1} = \beta(L)P_{t-1} = b_0 + b_1 P_{t-1} + \dots + b_n P_{t-n}. \quad (3)$$

The predictions defined by equation (3) are frequently used in applied econometric analysis as instruments for unobservable expectations (e.g., Wallis; Goodwin and Sheffrin). However, a different picture arises with regards to using the conditional variance of ϵ_t in (2) as a measure of risk. Specifically, if $h_t = \sigma^2$ for all t , then the conditional variance of ϵ_t is also σ^2 for all t . In other words, the conditional variance associated with the regression model in (1) does not vary over time and cannot be used in any formal way as a measure of risk for purposes of econometric estimation. Some authors, including Frenkel and Edwards, have simply used squared values of the innovations associated with regression equation (1) as a measure of risk. However, this procedure is inappropriate for modeling risk behavior in most agricultural settings because agents do not observe ϵ_t at the time production decisions are made.

Recently, Engle proposed a class of models known as autoregressive conditional heteroskedasticity (ARCH) models. The distinguishing feature of an ARCH process is that the forecast variance of a series P_t is allowed to vary systematically over time. Such models could be used to generate time-varying instruments for the conditional variance of P_t . The key feature is that the forecast variance, h_t , is conditioned on past realizations of P_t so that in general, an ARCH(p) model is written as $h_t = h(P_{t-1}, \dots, P_{t-p}, \alpha)$ where α is a vector of parameters to be estimated. The result is that conditional expectations of h_t can be obtained in much the same manner as the conditional forecasts of P_t in (3).

While Engle's ARCH process represents one useful alternative for estimating non-constant variance terms, in practice long lag lengths are frequently required to obtain stationarity. Realizing this, Bollerslev (1986) proposed an alternative to the ARCH model known as GARCH (generalized autoregressive conditional heteroskedasticity) processes. A GARCH process extends the information set Ω_{t-1} to include lagged values of h_t , as well as lagged values of P_t . Following Bollerslev, a GARCH(p, q) process is written as

$$h_t = \alpha_0 + \sum_{i=1}^q \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^p \beta_i h_{t-i}, \quad (4)$$

$$\text{where} \quad = \alpha_0 + A(L)\epsilon_{t-1}^2 + B(L)h_{t-1}$$

$$p \geq 0,$$

$$q \geq 0,$$

$$\alpha_0 \geq 0,$$

$$\alpha_i \geq 0, \quad i = 1, \dots, q, \text{ and}$$

$$\beta_i \geq 0,$$

$$i = 1, \dots, p.$$

The nonnegativity constraints associated with the parameters in the h_t equation are necessary to satisfy certain regularity conditions associated with the GARCH model. Also, for $p = 0$ the process reduces to an ARCH(q) model. Alternatively, for $p = q = 0$, the conditional variance is constant.

in standard time-series models, and the innovation ϵ_t simply reduces to white noise.

Bollerslev (1986) shows that a sufficient condition for the GARCH(p,q) process to be wide-sense stationary is that $A(1) + B(1) < 1$. The unconditional mean and variance of the innovation ϵ_t are then given by $E(\epsilon_t) = 0$ and $\text{var}(\epsilon_t) = \sigma_0^2(1 - A(1) - B(1))^{-1}$. Thus, for a stationary GARCH(p,q) process, the unconditional variance of ϵ_t is constant while the conditional variance can change over time. Finally, using equation (3) and the normality assumption in (2), it follows that the conditional subjective probability function of price is given by

$$P_t | \Omega_{t-1} \sim N[\beta(L)P_{t-1}, h_t(A(L)\epsilon_{t-1}^2, B(L)h_{t-1})]. \quad (5)$$

To summarize, if the data suggest that heteroskedasticity of the form implied by (4) is present, then instruments for subjective expectations of both price and price risk could be generated in a manner consistent with the GARCH(p,q) process. These instruments could, in turn, be used to estimate risk effects in an econometric model of supply response.

Estimation Procedure

Before proceeding, several observations regarding the use of GARCH models to estimate price and risk effects in econometric supply models are in order. Pagan recently concluded that using regressors generated from a stochastic model as instruments in the estimation of a structural equation can result in biased estimates of the parameters' standard errors. Hoffman subsequently proposed a generalized least squares estimation procedure to cope with the nonscalar disturbance matrix resulting from the use of generated regressors in a structural model. However, problems arising from the use of generated regressors can also be avoided by estimating the parameters of the GARCH model and the structural supply model jointly using maximum likelihood (ML) (Hoffman, p. 338).

The procedure used here then is to estimate the parameters of the supply equation simultaneously with the parameters of the GARCH process used to define producers' subjective probability distribution about uncertain prices. Specifically, let $y_t = f(P_t^e, \sigma_t^2, Z_t)$ denote acreage or production of some agricultural commodity where P_t^e is expected price, σ_t^2 is expected price variance, and Z_t is a vector of supply shifters. Assuming linearity, and making the usual stochastic assumptions, an empirical specification of the supply model for y_t is

$$y_t = a_0 + a_1 P_t^e + a_2 \sigma_t^2 + a_3 Z_t + \epsilon_{1t} \quad (6)$$

where ϵ_{1t} is a mean zero normally distributed error term with finite variance σ_{11} . From (1) and (2), it follows that the price equation used to generate the expectations in (6) can be written as

$$P_t = b_0 + \sum_{i=1}^n b_i P_{t-i} + \epsilon_{2t}. \quad (7)$$

Assuming that ϵ_{2t} follows a GARCH(p,q) process, then ϵ_{1t} and ϵ_{2t} are distributed jointly as

$$\underline{\epsilon}_t = \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{bmatrix} \sim N \left[\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{12} & h_t \end{bmatrix} \right] \quad (8)$$

where σ_{11} and σ_{12} are constants whose values are to be estimated and

$$h_t = \alpha_0 + \sum_{i=1}^q \alpha_i \epsilon_{2t-i}^2 + \sum_{i=1}^p \beta_i h_{t-i} \quad (9)$$

Moreover, the α and β parameter vectors must still conform to the nonnegativity restrictions associated with the GARCH(p,q) process in (4). Finally, the price and variance expectations included in supply equation (7) are given by

$$P_t^e = E(P_t | \Omega_{t-1}) = b_0 + \sum_{i=1}^n b_i P_{t-i} \quad (10)$$

and

$$\sigma_t^2 = \text{var}(P_t | \Omega_{t-1}) = h_t. \quad (11)$$

With the above assumptions, the system of equations in (6), (7), and (9) can be estimated using a nonlinear ML estimation routine. An "unconcentrated" log likelihood function must be used since changes in the variance-covariance matrix in (8) directly affect the values of the computed residuals, ϵ_{1t} and ϵ_{2t} . Apart from a constant term, the "unconcentrated" log likelihood function used to estimate the parameters of the structural equations is

$$L = \sum_{t=1}^T \log |J_t| - \frac{1}{2} \sum_{t=1}^T \log |\Sigma_t| - \frac{1}{2} \sum_{t=1}^T \underline{\epsilon}_t' \Sigma_t^{-1} \underline{\epsilon}_t \quad (12)$$

Here J_t denotes the Jacobian of the transformation from $\underline{\epsilon}_t = (\epsilon_{1t}, \epsilon_{2t})'$ to (P_t, P_t^e) and Σ_t is the variance-covariance matrix of $\underline{\epsilon}_t$ as defined in (8).

Given the normality of the error vector $\underline{\epsilon}_t$, it follows that the resulting parameter estimates will have the usual desirable asymptotic properties. Moreover, the above system is similar in many respects to the multivariate GARCH process described by Engle and Bollerslev. The only difference is that the variance and covariance terms σ_{11} and σ_{12} are held constant for purposes of the present analysis. Finally, the structural model defined by equations (6) through (11) is similar to the rational expectations models considered by Wallis and others. In particular, note that the parameters in the conditional price and variance equations (10) and (11) are shared by both the supply equation (6) and the price equation (7). The

resulting cross-equation restrictions are consistent with the rational expectations hypothesis. Hence, the above system can be viewed as the logical extension of the rational expectations hypothesis to include risk terms.

III. Model Specification

The above approach was used to estimate a risk-responsive supply model for the U.S. broiler industry. Specifically, a two-equation price-production model is specified and estimated. The supply equation is similar to the one reported by Aradhyula and Holt (1989) and is specified as

$$\begin{aligned} QBP_t = & a_0 + a_1 D_{1t} + a_2 D_{2t} + a_3 D_{3t} + a_4 D_{4t} + a_5 WPB_t^e \\ & + a_6 WPB_t^v + a_7 PBF_{t-1} + a_8 HATCH_{t-1} + a_9 QBP_{t-4} + \epsilon_{1t} \end{aligned} \quad (13)$$

where QBP_t is broiler production in period t , million pounds; D_{jt} is a quarterly dummy variable, $j = 1, \dots, 4$; WPB_t^e is the expected real wholesale price of broilers in time t , viewed from period $t-1$, dollars per cwt.; WPB_t^v is the expected variance of the real wholesale price of broilers in time t , also viewed in time $t-1$; PBF_{t-1} is the real price of broiler feed in $t-1$, cents per pound; and $HATCH_{t-1}$ denotes the hatch of broiler type chicks in commercial hatcheries in period $t-1$, thousand head.

Because it takes approximately two months for broilers to reach a marketable weight, it follows that current quarter production depends on the expectations formed by producers in the previous period. The only input price included in the supply equation is the price of feed, PBF_{t-1} , since feed costs account for roughly 75% of total variable production costs. In the present study, PBF_{t-1} was determined as a weighted average of the prices of corn and soybean meal where the weights were 0.70 and 0.30, respectively.^{3/} All prices in the supply equation were deflated by the Consumer Price Index.

In the short run, broiler production also depends on the number of broiler-type chicks available. This relationship is captured in the supply equation by including the variable $HATCH_{t-1}$. Finally, lagged production was included in the specification because broiler producers may not be able to fully adjust production levels to desired levels during any given quarter.^{1/}

Preliminary analysis revealed that real wholesale broiler prices could be adequately represented by a fourth-order autoregressive model. In addition, a time trend was included to ensure stationarity. The price equation used is then given by:

$$(1 - b_1 L - b_2 L^2 - b_3 L^3 - b_4 L^4) WPB_t = b_5 t + \epsilon_{2t} \quad (14)$$

where L is a polynomial lag operator such that $L^s WPB_t = WPB_{t-s}$ and t denotes a linear time trend.

The specification of the GARCH process begins with an examination of the residuals ϵ_{2t} generated from the AR(4) broiler price equation. The Ljung-Box portmanteau Q-statistic associated with the ϵ_{2t} residual series was 10.56 which is well below the critical value of 18.31 from the asymptotic χ^2 distribution at 10 degrees of freedom. Thus, the hypothesis that the residuals from the estimated AR(4) model are white noise cannot be rejected.

The same test was then performed using squared values of the residuals

ϵ_{2t} . As reported by McLeod and Li, the portmanteau test statistic $Q^2(m)$ derived from the squared innovations will be distributed asymptotically as a χ^2 distribution with m degrees of freedom. The resulting Q^2 statistic at ten degrees of freedom was 28.87 which is significant at the 5% level. The absence of serial correlation in the conditional first moment of broiler price coupled with the presence of serial correlation in the conditional second moment is one of the implications of the GARCH(p,q) process (Bollerslev, 1987).

While standard Box-Jenkins procedures can be used to identify the appropriate order of the GARCH process (Bollerslev, 1988), a more pragmatic approach was adopted here. Specifically, the broiler price equation was fitted initially as a GARCH(1,1) process. Other low-order GARCH models were then estimated and examined for overall improvement in model fit and parameter significance. The results of this exercise indicated that a simple GARCH(1,1) model was adequate. Consequently, the GARCH model used in the subsequent empirical analysis is given by

$$h_t = \alpha_0 + \alpha_1 \epsilon_{2t-1}^2 + \beta_1 h_{t-1} \quad (15)$$

where the parameters α_0 , α_1 , and β_1 are constrained to be nonnegative and $\alpha_1 + \beta_1 \leq 1$ must hold for the GARCH(1,1) model to be wide-sense stationary.

IV. Estimation Results

The Davidon-Fletcher-Powell (DFP) algorithm was used to obtain maximum likelihood estimates the two-equation production-price model for the U.S. broiler industry. Parameter estimates were obtained using quarterly data from the 1969-1986 time period. All cross-equation restrictions implied by the expectations assumptions outlined in (6)-(11) were incorporated in the estimation. The ML estimates of the broiler model with price risk and GARCH-generated expectations are presented in table 1.

Of interest is that all of the estimated coefficients of the conditional variance equation h_t are significant at standard levels. This implies that the conditional variances associated with the one-step-ahead broiler price predictions are time-varying. Also, all parameters in the production equation have theoretically correct signs. Importantly, the sign on the estimated coefficient for expected price WPB_t^e is positive while the sign on the

estimated coefficient for expected price variance WPB_t^v is negative. The estimated coefficient for expected price is also significant at all usual levels while a one-tailed test on the risk coefficient indicates significance at the 0.10 level. All other estimated coefficients associated with economic variables are significant at usual levels. The estimated production equation also fits the data well, as indicated by the high R^2 (0.98).

Short- and long-run elasticities of supply with respect to specific economic variables of interest are reported in table 2 under the row labeled GARCH. The implied short-run elasticity of supply with respect to the expected price of broilers is 0.22 in the short run and 0.55 in the long run. Likewise, the short-run supply elasticity with respect to the variance of broiler price is -0.012 in the short run and -0.03 in the long run. Finally, the supply elasticity with respect to the lagged feed price is -0.047 in the short run and -0.117 in the long run. All estimated supply elasticities are

well within the range of previous estimates (e.g., Chavas and Johnson; Aradhyula and Holt, 1989).

For purposes of comparison, the above supply equation was also estimated using the generalized adaptive expectations procedure developed by Just. The adaptive expectations model provides a reasonable comparison with the GARCH model since both imply an infinitely declining lag structure on the squared deviations between observed and expected prices. Using Just's notation, expected price in period t for the adaptive expectations model is given by

$$WPB_t^e = \theta \sum_{k=0}^{\infty} (1 - \theta)^k WPB_{t-k-1} \quad (16)$$

where θ is a scalar parameter constrained to lie in the positive unit interval $(0,1)$. In a similar fashion, the adaptive expectations measure for price risk is defined as

$$WPB_t^v = \phi \sum_{k=0}^{\infty} (1 - \phi)^k [WPB_{t-k-1} - WPB_{t-k-1}^e]^2 \quad (17)$$

where ϕ is a scalar parameter also constrained to lie in the $(0,1)$ interval. Just outlines a procedure for estimating a supply equation where the mean and variance of expected price are given by (16) and (17), respectively. In short, his method combines a two-dimensional grid search over the θ and ϕ parameter space with conditional least squares to obtain the ML estimates of the supply parameters and the scalars θ and ϕ . See Just for further details.

The parameter estimates of the supply equation with adaptive expectations for both the mean and variance of price are presented in table 3. The results are similar to those obtained using a GARCH process. In particular, the estimated coefficients for the expected price and expected variance terms are positive and negative, respectively. Moreover, the estimated coefficient for expected price is significant at all usual levels of significance. A one-tailed test on the estimated risk coefficient indicates significance at the 0.05 level. This model also fits the data well as indicated by an R^2 value of 0.99.

Short- and long-run elasticities of supply for the adaptive expectations model are also reported in table 2. In general, the elasticities are similar in magnitude to those obtained for the GARCH model. Interestingly, the short-run risk elasticity obtained with the adaptive expectations model is nearly half that obtained using the GARCH model. Likewise, the corresponding long-run risk elasticity is nearly one third the size of the long-run risk obtained from the GARCH model.

A plot of the variance terms implied by both the GARCH and the adaptive expectations models is provided in figure 1. In general, the adaptive expectations measure of price risk indicates more volatility in real broiler prices than does the corresponding conditional variances implied by the GARCH model. Both measures reflect the turbulence in wholesale broiler prices experienced in the early 1970s, but the highest variance implied by the adaptive expectations model is six times larger than the highest variance term implied by the GARCH model. One possible explanation for these large discrepancies is the differences in the lag structures associated with the squared price deviations in each estimated model. For instance, the first-period lag weight associated with ϵ_t^2 in the GARCH model is 0.16 while the same lag weight from the adaptive expectations model is 0.23. Furthermore, the lag weights associated with the squared innovations in the GARCH model remain well

below those implied by the adaptive expectations model for the first eleven periods. The implication is that the adaptive expectations model will reflect price shocks faster than will the estimated GARCH model.

V. Conclusions

This paper has explored the potential for using a new method for estimating risk effects in aggregate agricultural supply equations. Specifically, a new time-series procedure known as GARCH processes was presented as an alternative for modeling producers' subjective price and risk expectations. GARCH models differ from standard time-series models in that the conditional variance of the underlying stochastic process is specified as a function of past realizations of the random variable of interest. The result is that the conditional variance derived from a GARCH process will over time.

The resulting framework was used to estimate a supply model for the U.S. broiler industry where producer expectations about both the mean and variance of price were determined using a GARCH(1,1) model. The estimated supply equation was then compared with a supply equation estimated using Just's adaptive expectations framework. The results are favorable in that both models indicate that price risk is an important component of broiler production; however, the question of which model is "best" is currently left unanswered. In summary, the results obtained here are encouraging in that GARCH models can apparently be used as one viable alternative for generating proxy variables for unobservable price and variance expectations.

Endnotes

- 1/ For instance, Antonovitz and Green estimated moving ARIMA models to obtain time-varying estimates of price risk in a supply model for fed beef. A chief disadvantage of this approach is that a large amount of presample data are typically needed to initialize the process.
- 2/ Note that the determinant of J_t is everywhere equal to unity in the present model. Hence, the first term in the log likelihood function (12) will vanish.
- 3/ These weights are identical to those used by Chavas and Johnson in their analysis of broiler supply response. They reflect the relative importance of corn and soybean meal, respectively, in a typical broiler ration.
- 4/ The four-quarter lag on the dependent variable in the supply equation is consistent with the specifications used by Chavas and Johnson and Aradhyula and Holt (1989).

Table 1. Maximum Likelihood Estimates of a Structural Model of the U.S. Broiler Market with GARCH Generated Expectations.

Broiler Production:

$$\begin{aligned} QBP_t = & -102.286D_{1t} - 107.302D_{2t} - 120.046D_{3t} - 112.726D_{4t} + 2.643WPB_t^e \\ & (20.285) \quad (21.072) \quad (21.535) \quad (20.410) \quad (0.605) \\ & - 0.510WPB_t^v - 4.390PBF_{t-1} + 1.866HATCH_{t-1} + 0.599QBP_{t-4} + \epsilon_{1t} \\ & (0.343) \quad (1.423) \quad (0.206) \quad (0.064) \end{aligned}$$

$$R^2 = 0.980$$

Broiler Price:

$$\begin{aligned} (1 - 0.524B - 0.134B^2 - 0.135B^3 - 0.148B^4)WPB_t = & 0.657 + 0.008t + \epsilon_{2t} \\ & (0.093) \quad (0.097) \quad (0.091) \quad (0.075) \quad (2.498) \quad (0.015) \end{aligned}$$

$$\begin{aligned} h_t = & 1.320 + 0.160 \epsilon_{2t-1}^2 + 0.603 h_{t-1} \\ & (0.677) \quad (0.078) \quad (0.155) \end{aligned}$$

$$R^2 = 0.700$$

$$\begin{aligned} \sigma_{11}^2 = & 28.400 \\ & (5.409) \end{aligned} \quad \begin{aligned} \sigma_{12} = & 4.905 \\ & (1.906) \end{aligned}$$

$$\text{Log - Likelihood} = -245.068$$

Note: Figures in parantheses are asymptotic standard errors. B is a lag operator such that $B^s X_t = X_{t-s}$.

a/ WPB_t^e is equal to the conditional expectation of broiler price as implied by the AR(4) price equation. Likewise, the expected price variance, WPB_t^v , is equal to the conditional price variance h_t .

Table 2: Elasticities of Broiler Production Evaluated at the Sample Means
1969-86.

Model	WPB_t^e		WPB_t^v		PBF_{t-1}	
	Short Run	Long Run	Short Run	Long Run	Short Run	Long Run
1. GARCH Expectations	0.222	0.554	-0.012	-0.030	-0.047	-0.117
2. Adaptive Expectations	0.225	0.456	-0.005	-0.010	-0.059	-0.120

Table 3. Maximum Likelihood Estimates of a Broiler Production Model with Adaptive Expectations.

Broiler Production:

$$QPB_t = - \frac{116.719D_{1t}}{(14.581)} - \frac{120.798D_{2t}}{(15.279)} - \frac{136.423D_{3t}}{(15.401)} - \frac{126.105D_{4t}}{(14.892)} + \frac{2.742WPB_t^e}{(0.441)} \\ - \frac{0.087WPB_t^v}{(0.050)} - \frac{5.534PBF_{t-1}}{(1.335)} + \frac{2.231HATCH_{t-1}}{(0.157)} + \frac{0.506QBP_{t-4}}{(0.054)} + \epsilon_t$$

Expected Price:

$$WPB_t^e = 0.413 \sum_{k=0}^{\infty} (1 - 0.413)^k WPB_{t-k-1}$$

Expected Variance:

$$WPB_t^v = 0.364 \sum_{k=0}^{\infty} (1 - 0.364)^k [WPB_{t-k-1} - WPB_{t-k-1}^e]^2$$

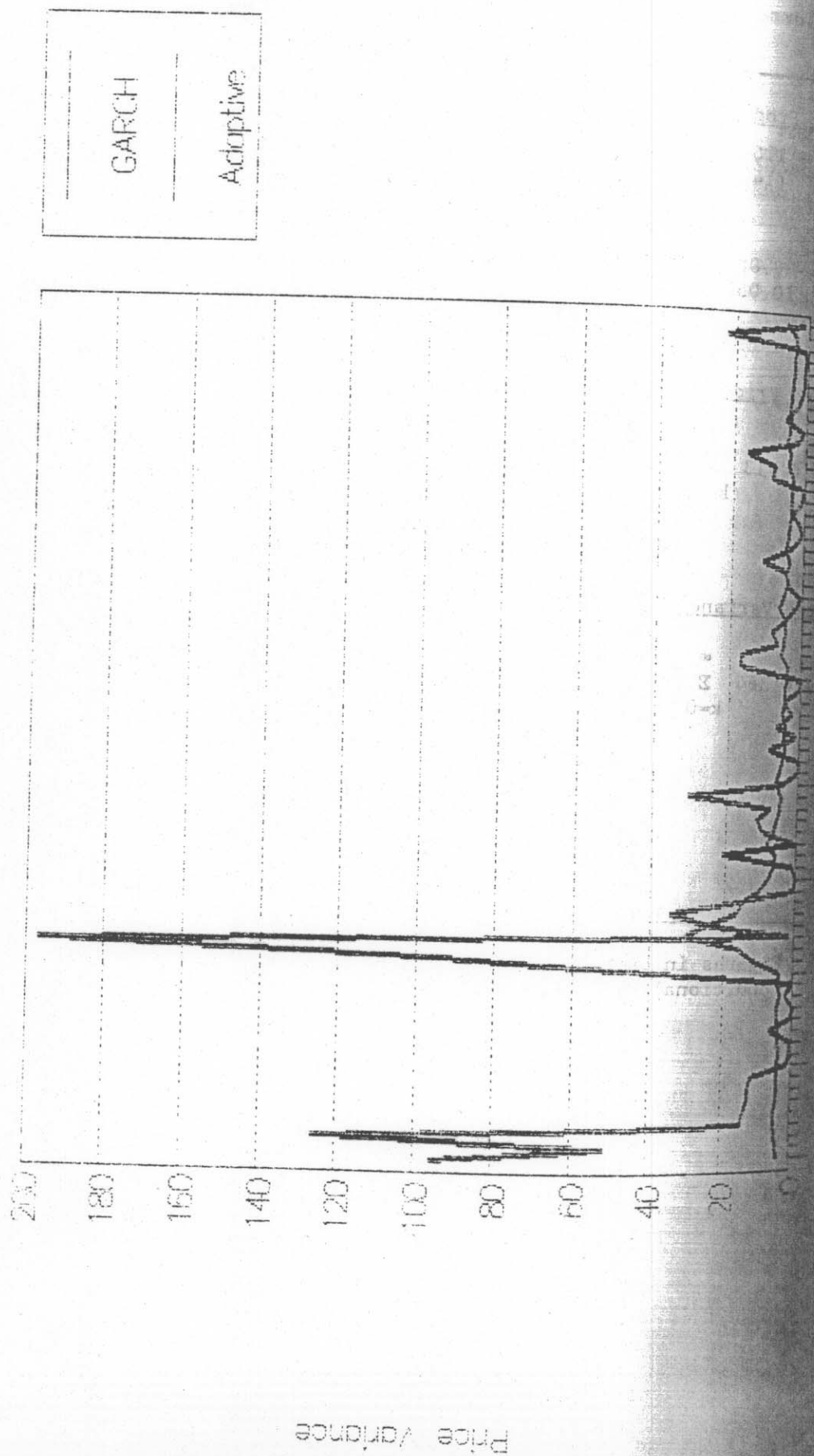
$$\text{Log - Likelihood} = -214.770$$

$$R^2 = 0.993$$

$$\sigma^2 = 22.827$$

Note: Figures in parantheses are standard errors obtained from the conditional least-squares estimates.

Figure 1. Variance of Wholesale Broiler Prices, 1969-1986.



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