Optimal Grazing Pressure under Output Price and Production Uncertainty with Alternative Functional Forms

By

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ABSTRACT

This study uses a Cox parametric bootstrap test to select between two specifications of the von Liebig hypothesis, a switching regression model and a non-linear mixed stochastic plateau function. The selected production function was used to determine optimal stocking density for dual-purpose winter wheat, under production and output price uncertainty. The switching regression approach was rejected in favor of the non-linear mixed stochastic plateau function. The relatively small difference in optimal stocking density between risk aversion and risk neutrality suggests that risk-aversion is much less important in explaining producer response to uncertainty than is nonlinearity in the production function.

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Producing winter wheat for both grazing and grain is an important economic activity in the US plains. The stocking decision is traditionally made without the benefit of a decision aid such that some surveys (see True, Epplin, Krenzer, and Horn) put average farmer stocking densities far below recommended levels. This apparently contrasts with findings by Kaitibie et al., that stocking density for dual-purpose wheat should be on the upside because understocking is more costly than overstocking. In addition, low stocking densities could lead to underutilization of resources while high stocking densities could result in low gain per animal.

Farmers generally make stocking decisions under output price and production uncertainty. However, the very limited literature on dual-purpose winter wheat production has focused mainly on deterministic situations (Hart et al.; Torell, Lyon and Godfrey), sometimes on production uncertainty (Kaitibie et al.), but rarely on price uncertainty. But there is no common agreement as to what one can expect from a risk-averse producer facing a stochastic world that is defined by both output price and production uncertainty (Chambers and Quiggin). Price uncertainty has particularly become important in recent years with increased incidence of microbial shedding, farm-level food safety concerns and related price discount cases.

Livestock grazing practices generally follow patterns that can be explained by the von Liebig hypothesis, characterized by non-substitution between inputs and a gain/yield plateau. Several studies (Kaitibie et al.; Pinchak et al.; Redmon et al.) have shown a linear response plateau function between average daily gain and forage allowance. In addition Kaitibie et al. showed that the plateau could be stochastic. Kaitibie et al.

considered only the linear response plateau function of Tembo, Brorsen and Epplin (TBE), and did not consider the alternative linear response plateau specification of Berck and Helfand, and Paris (BHP). Both approaches are considered here, and this research provides the first empirical comparison of the two competing approaches. The two models are not nested, and also differ in their treatment of the error terms. As Barrett and Li note, switching regression approaches such as that used by BHP are not predictive models. Thus a switching regression model cannot identify which locations or years were high or low, and it can be sensitive to non-normality. On the other hand the TBE model makes it possible to identify unusually high or low yields by estimating random effects for each year.

The importance of functional form in empirical production and consumption studies is widely documented (Paris; Ackello-Ogutu, Paris and Williams; Frank, Beattie and Embleton). Problems such as varying elasticity estimates between functional forms often occur (see Dameus at al.). In nutrient response functions, polynomial specifications often result in higher fertilizer recommendations (Chambers and Lichtenberg). In recent times, nested and non-nested hypotheses tests have been used to dissuade researchers from arbitrarily selecting functional forms. Paris used the *P*-test by Davidson and MacKinnon to select between a non linear von Liebig switching regression model and a tractable Mitscherlich-Baule function, and a likelihood ratio test to select between linear and non linear von Liebig models with Mitscherlich-Baule specifications for the response function.

In this study, a Cox nonnested parametric bootstrap procedure developed by Coulibaly and Brorsen is used to discriminate between the switching regression model of

PBH and the non-linear mixed model of TBE. Unlike other versions of the Cox test developed by Pesaran and Deaton, and Pesaran and Pesaran, the Cox nonnested parametric boostrap gives a test statistic with correct size and high power even in small samples, without loss of generality (Coulibaly and Brorsen; Dameus et al.). Furthermore, a model of production decision-making for the expected utility maximizing firm under production and output price uncertainty is applied to dual-purpose winter wheat production using the appropriately selected functional form. The farmer is assumed to exhibit a von-Neumann Morgenstern utility function that is defined on wealth.

Revenue is derived from both wheat grain and beef gain. To formulate the producer's profit function, the effect of stocking density on wheat grain yield was evaluated by Kaitibie et al. The determination that stocking density does not affect wheat grain yield is consistent with other studies such as Christiansen, Svejcar and Phillips, and Redmon et al. (1996). Therefore, only expected returns from beef gain would be used to determine optimal stocking density.

The von Liebig Production Functions

Following the von Liebig law of the minimums, that crop yield is in direct relation to the amount of the most limiting soil nutrient, different versions of the production function have been postulated. For instance, following Paris and Knapp's definition of an empirically tractable version of the von Liebig production function, we represent a univariate linear response plateau as

$$y_i = \min\{f_1(x_{1i}, \beta_1), P\} + u_i, \tag{1}$$

where $f_1(.)$ is a linear response function, P is the plateau and u_i represents the random error term. When a univariate production function is implied, the independent variable is assumed to be the non-limiting input.

The switching regression approach to estimating a von Liebig production function was used by Berck and Helfand, and Paris, following Maddala and Nelson

(2) $$y_{jt} = \min\{f_1(x_{1jt}, \beta_1) + u_{1jt}, P + \pi_{jt}\},$$

where $f(.)$ is the response function, P is the plateau, and u_{1jt} and π_{jt} are normally distributed random error terms, correlated for the same plot time and time, but not correlated across plot and time.

Using a Mitscherlich-Baule specification and a linear von Liebig specification for the response function, Paris used a likelihood ratio test to support the conclusion that the switching regression model, for instance (2), is preferred to model (1). In addition, the *J* and *P* tests of Davidson and MacKinnon were used to show that yet again, the switching regression model was superior to the Mitscherlich-Baule production function.

An alternative specification of the von Liebig production function is the non linear mixed model of Tembo, Brorsen and Epplin:

(3) $$y_{jt} = \begin{cases} f_1(x_{1jt}, \beta_1) + u_{1jt} & \text{if } x_1 \le x_1^* \\ P + \pi_{jt} & \text{otherwise.} \end{cases}$$

This model deviates from two major simplifications that characterize the switching regression model and other specifications of plateau response functions: year effects and the plateau are treated as random components. Thus $u_{njt} = \varepsilon_{jt} + u_t, n = 1,...N$, and $\pi_{jt} = \varepsilon_{jt} + u_t + v_t$, where ε is the pure random error, u is the year random effect and v is the error term associated with the plateau. In addition, for the TBE model,

$\operatorname{cov}(u_{kjt}, u_{sjt}) = \sigma_u^2 \ \forall\ k \neq s$ and $n \neq j$, and $\operatorname{cov}(\pi_{nt}, \pi_{jt}) = \sigma_\varepsilon^2 + \sigma_v^2 \ \forall\ n \neq j$. In the BHP approach the latter terms are restricted to zero. Unlike the switching regression approach the linear response plateau function is estimated by directly maximizing the marginal log-likelihood function. Neither model (2) nor model (3) is a special case of the other (Tembo, Brorsen and Epplin), therefore a nonnested test for functional form is appropriate. A major weakness of the TBE model is getting convergence to occur.

Grazing pressure is a function of stocking density, and is defined as carrying capacity in steer-days per metric ton of forage. Average daily gain was estimated as a univariate function of forage allowance. Forage allowance is a decision variable defined as the amount of available forage per steer-day of grazing (Hart; Torell, Lyon and Godfrey). When the determinants are defined in identical units, forage allowance is the inverse of grazing pressure.

When (2) is the correct functional form, the model to simulate is:

$$ADG = \min(0.5001 + 50.5474FA + u, 1.0621 + \pi). \tag{4}$$

This model was estimated with the non-linear mixed procedure in SAS which uses a finite difference approximation to estimate the cumulative density functions of the normal distribution, for each regime. Equation (4) is a two-regime switching regression model. When (3) is the correct functional form, the model to simulate is (see Kaitibie et al.):

$$ADG = \begin{cases} 0.4812 + 66.4665FA + \varepsilon + u & \text{if } FA < 0.0105 \\ 1.1798 + \varepsilon + u + v & \text{otherwise.} \end{cases} \tag{5}$$

Where applicable, all distributional assumptions for variables and error terms are based on normality. The parameter estimates for both models, as well as estimates of the error components are given in Table 1.

The data used for estimating the models were obtained from a stocking density experiment at the Expanded Wheat Pasture Research facility near Marshall, Oklahoma. Seven years of data on gain per steer per day and average forage production over the grazing period were used. Detailed information on experimentation and data collection has been reported by Horn et al.

Analytical Framework

Regression models are said to be nonnested if no one model can be written as a special case of the other. Under the null hypothesis, consider for instance, a single equation, possibly non-linear regression model of the form

(6) $$H_0 : y_i = f_i(X_i, \beta) + \varepsilon_{0i},$$

where y_i is the ith observation on the dependent variable, X_i is a vector of observations on exogenous variables, β is a k vector of parameters to be estimated, and the error term $\varepsilon_{0i} \sim N(0, \sigma^2_{\varepsilon 0i})$ when the null hypothesis is true. Consider another regression model of the form

(7) $$H_1 : y_i = g_i(Z_i, \gamma) + \varepsilon_{1i},$$

where Z_i is a vector of observations on exogenous variables, γ is an l vector of parameters to be estimated, and $\varepsilon_{1i} \sim N(0, \sigma^2_{\varepsilon 1i})$ when the alternative hypothesis is true. Based on the assumption that equation (6) cannot be written as a special form of equation (7), and equation (7) cannot be written as a special form of equation (6), several tests have been proposed to test the truth of the null hypothesis. Among them, is the Cox parametric bootstrap procedure by Coulibaly and Brorsen. The applicability of this test, and its performance relative to other Cox type tests is presented in Coulibaly and Brorsen, and in Dameus et al.

Coulibaly and Brorsen's Parametric Bootstrap Procedure

The Cox test is essentially carried out by computing the difference between the log-likelihood values of two models under consideration when the null hypothesis is true. When testing the null hypothesis against the alternative hypothesis, the Cox test statistic takes the general form

(8) $$T_0 = L_{01} - E_0(L_{01}),$$

where T_0 is an asymptotically distributed test statistic with zero mean and variance v_0^2 under the null hypothesis. The value $L_{01} = L_0(\hat{\theta}_0) - L_1(\hat{\theta}_1)$ is the difference in the log of the likelihood ratios under the null hypothesis and the alternative hypothesis, and $E_0(L_{01})$ is the expected value of L_{01} under the null hypothesis. In addition the values $\hat{\theta}_0$ and $\hat{\theta}_1$ are maximum likelihood parameter estimates of the models under consideration, under the null hypothesis and the alternative hypothesis, respectively. Following similar definitions, the Cox statistic can also be derived when testing the alternative hypothesis against the null hypothesis, so that

(9) $$T_1 = L_{10} - E_1(L_{10}) .$$

Because of the difficulty of obtaining analytical formulas for $E_0(L_{01})$ and v_0^2, Pesaran and Deaton proposed a version of the Cox test which uses transformed dependent variables for testing linear against log-linear models. This test statistic, upon which Davidson and MacKinnon's *P* test is based, often has incorrect sizes in small samples.

The alternative test proposed by Coulibaly and Brorsen used a parametric bootstrap procedure to obtain a test statistic with high power and correct size, in small and in large samples. The test statistic is not asymptotically pivotal.[1] However, the tests are at least as good as a parametric bootstrap based on Pesaran and Pesaran's asymptotically pivotal statistic (Coulibaly and Brorsen). It is based on the likelihood ratio of the two models under consideration, and uses the parametric bootstrap to estimate the distribution of the test statistic under the null hypothesis (Dameus et al.).

The parametric bootstrap procedure uses parameter estimates from the model under the null hypothesis to generate Monte Carlo samples, using the same number of observations as the original data. The procedure by Coulibaly and Brorsen uses actual and generated data to compute a *p*-value

(10) $$p-value = \frac{\left(numb\left[L_0\left(\hat{\theta}_{0j}, \mathbf{y}_j\right) - L_1\left(\hat{\theta}_{1j}, \mathbf{y}_j\right) \leq L_{01} \ \forall \ j = 1, \ldots, N\right] + 1\right)}{N+1}$$

where *numb*[.] represents the number of realizations for which the specified relationship is true, *N* is the number of samples of size *T* generated under each model, and L_{01} is the actual value of the log-likelihood ratio. The values $L_0(.)$ and $L_1(.)$ respectively represent the values of the log-likelihood function with the generated data under the null and the alternative hypotheses. Coulibaly and Brorsen suggest adding the value of one to both the numerator and the denominator as a small sample correction. Coulibaly and Brorsen's *p*-value estimates the area to the left of the Cox test statistic L_{01}. Generally, the null hypothesis would be rejected if the *p*-value is small.

[1] An asymptotically pivotal statistic is a statistic whose asymptotic distribution does not depend on unknown parameters.

Dameus et al., list the steps involved in using the Cox test with parametric bootstrap procedure to select between two functional forms: (*a*) the two models under consideration are estimated using the actual data set; (*b*) the likelihood values of the two models are used to compute the actual likelihood ratio of the two models; (*c*) based on the assumption that the null hypothesis is the true model, a distribution function is estimated for the original data, and based on this estimate, a large number of data sets of the same size is generated; (*d*) the two models are re-estimated for each of the generated data sets; (*e*) the simulated log-likelihood ratio for each simulated data set is computed; and (*f*) the true and simulated log-likelihood ratios are compared and used to compute the *p-value* in equation (10). The test procedure requires that steps (*c*) to (*f*) be performed twice, once when the switching regression is the true model, and when the non-linear mixed model is the true model.

Results of the Cox Parametric Bootstrap Test

Results of the parametric bootstrap test are given in Table 2. Convergence problems associated with the linear response stochastic plateau make it difficult to follow the recommendations of Coulibaly and Brorsen, suggesting that with a sample of 81, the ideal number of replications would be between 500 and 1000. Therefore a less than ideal number of 20 replications was carried out. However as Table 2 suggests, the *p*-value of 1.000 when the TBE model is true under the null suggests that no additional replications needed to be undertaken. The Cox parametric bootstrap test shows that the two-regime switching regression of Paris, and Berck and Helfand, can be rejected in favor of the linear response stochastic plateau function of Tembo, Brorsen and Epplin. Therefore, the expected utility maximization framework to determine optimal stocking density under production and output price uncertainty was carried out based on equation (5).

Expected Utility Maximization

A model of production decision-making for the expected utility maximizing firm under production and output price uncertainty is applied to dual-purpose winter wheat production. The farmer is assumed to exhibit a von-Neumann Morgenstern utility that is defined on wealth, such that $U'(W) > 0$ and $U''(W) < 0$. It is further assumed that the farmer's decision making is best characterized by an exponential utility function of the form $U(W) = 1 - e^{-bW}$, where b is the Arrow-Pratt coefficient of absolute risk aversion. The exponential utility function describes a generally conservative entrepreneur, exhibiting constant absolute risk aversion. This analysis was carried out using a risk aversion parameter of 0.00005, following King and Oamek's definition of a risk-averse dryland wheat farmer based on whole-farm data.

To obtain total gain in kg per hectare, average daily gain is multiplied by grazing pressure, the inverse of forage allowance. Therefore, using the indicator function defined as

(11) $$\mathrm{I}_{(-\infty,\,\mathrm{GP}^{-1})}(FA_{\mathrm{critical}}) = \begin{cases} 1, \text{if } \mathrm{FA}^{*} \leq GP^{-1} \\ 0, \text{otherwise} \end{cases}$$

the total gain function with respect to equation (5) is re-written as

(12) $$TG = \left\{(\alpha_0 GP + \alpha_1)(1 - \mathrm{I}_{(-\infty,\mathrm{GP}^{-1})}(FA^{*})) + ADG_{\max} GP\, \mathrm{I}_{(-\infty,\mathrm{GP}^{-1})}(FA^{*})\right\} + \varepsilon \text{ x } GP.$$

This total gain function has distinct mean and variance components, and follows a specification that resembles the Just and Pope model, $ADG = f(GP) + h(GP)\varepsilon$, where

$f(GP)$ is the mean equation or the expected value of total gain, and $h(GP)\varepsilon$ is the variance equation.

Assuming that $E\left(\mathrm{I}_{(-\infty,\mathrm{GP}^{-1})}\left(FA^*\right)\right) = F\left(GP^{-1}\right)$, expectations about total gain are taken such that the mean equation $f(GP)$ becomes

$$(13) \qquad f(GP) = (\alpha_0 GP + \alpha_1)\left(1 - F\left(GP^{-1}\right)\right) + \int_{-\infty}^{GP^{-1}} \left(\alpha_0 + \alpha_1 FA^*\right) GP\, f\left(FA^*\right) dFA^*,$$

where the function $F(.)$ is the cdf of FA^* evaluated at GP^{-1}. From equation (12) it follows that the variance equation $h(GP)\varepsilon$ is $GP\varepsilon$, so that $h(GP) = GP$.

Based on the assumption that wealth is the sum of initial wealth and profit that accrues to steer production because stocking density has no significant effect on wheat grain yield under good grazing practices, the farmer would maximize

$$(14) \qquad \max EU(W \mid GP) = EU(W_0 + (\overline{P} + \theta) \times \left[f(GP) + h(GP)\varepsilon\right] - rGP)$$

where r is the marginal steer carrying cost, estimated at \$0.67 per steer-day. $\overline{P}$ is the expected value of gain. Value of gain is used as a proxy for observed price in livestock gain studies. The value θ is the random component of the value of gain P, and σ_θ^2 is the variance. USDA quoted prices and data from Marshall, Oklahoma, were used to calculate values for P, using the expression

$$(15) \qquad P = \frac{\left[\text{Sale Price x }\left(\text{Initial wt} + \text{Grazing Period x ADG}\right)\right] - \left(\text{Initial wt x Pur. Price}\right)}{\text{Grazing Period x ADG}}.$$

The estimated value of $\overline{P}$ is \$1.36 per kg, with a variance of 0.32560. A Taylor series approximation to the marginal utility of grazing pressure is necessary to determine the effects of output price and production uncertainty on optimal stocking density.

The relationships that follow using a production function similar to the specification of Just and Pope, are attributed to Isik. If θ and ε are assumed to be independent, then the value of marginal gain may be defined as

(16) $$\overline{P}f'(GP) = \frac{\phi h(GP)h'(GP)\sigma_{\varepsilon}^{2}\left(\overline{P}^{2} + \sigma_{\theta}^{2}\right) + r}{1 - \left(\phi\sigma_{\theta}^{2} f(GP)\right)/\overline{P}},$$

where $\phi = -U''(W)/U'(W)$ is the Arrow-Pratt coefficient of absolute risk aversion. For the risk neutral situation where $\phi = 0$, the value of marginal gain equals the marginal input cost, $\overline{P}f'(GP) = r$. The optimal grazing pressure is one that solves equation (16) under risk aversion, or one that equates marginal value of gain with marginal input cost when the decision maker is risk neutral. The optimal stocking density is then derived from the relationship *GP* =(*t* x *SD*)/*F* (see Hart et al.; Torell, Lyon and Godfrey), where *t* is the length of the grazing period, *SD* is stocking density and *F* is the amount of available forage. Isik also shows that additive production uncertainty does not affect input use. The results are presented in Table 3.

Table 3 shows that under risk neutrality, the optimal stocking density is 0.8704 steers per hectare, and 0.8693 steers per hectare under risk aversion, and production and output price uncertainty. Evident in equation (16) above, the results show a marginal decline in stocking density from risk neutrality to risk aversion, so that as risks increase rationality dictates a decrease in input use, when the input is risk increasing, as grazing pressure is in this case.

The optimal profit under risk aversion was estimated at $250 per hectare. Under non-optimal stocking (obtained in Table 3 by reducing optimal grazing pressure by 10 units and then increasing optimal grazing pressure by 10 units), it is clear that the cost of (non-optimal) understocking at $8.01 per hectare is higher than the cost of (non-optimal) overstocking at $3.52 per hectare.

Conclusions

The importance of this study is twofold: first to discriminate between two functional forms that follow the von Liebig hypothesis using a Cox parametric bootstrap test that gives a test statistic with correct size and high power even in small samples, without loss of generality; and second, to determine the optimal stocking density for dual purpose winter wheat under production and output price uncertainty using the selected functional form.

Test results rejected the switching regression model with only spatial variability in favor of the linear response plateau of Tembo, Brorsen and Epplin for the data set. When the latter was used in an expected utility maximization framework, under production and output price uncertainty, we estimated an optimal stocking density of 0.8693 steers per hectare under risk aversion, and 0.8704 steers per hectare under risk neutrality. The difference in stocking density between risk aversion and risk neutrality is small. Therefore risk aversion is much less important in explaining producer response to uncertainty than is non-linearity in the production function. The research on risk in agricultural economics has been looking in the wrong place.

It is not unusual to use parameter estimates from all functional forms under consideration to determine optimality conditions. However, since this study also involved a non-nested hypothesis test for functional form, determining optimality conditions for the rejected functional form was considered unnecessary.

REFERENCES

Ackello-Ogutu, C., Q. Paris, and W.A. Williams. "Testing a von Liebig Crop Response Function Against Polynomial Specifications." *American Journal of Agricultural Economics* 67(November 1985):873-880.

Barrett, C.B., and J.R. Li. "Distinguishing between Equilibrium and Integration in Spatial Price Analysis." *American Journal of Agricultural Economics* 84(May 2002):292-307.

Berck, P., and G. Helfand. "Reconciling the von Liebig and Differentiable Crop Production Functions." *American Journal of Agricultural Economics* 72(November 1990):985-996.

Chambers, R.G., and E. Lichtenberg. "A Nonparametric Approach to the von Liebig-Paris Technology." *American Journal of Agricultural Economics* 78(May 1996):373-386.

Chambers, R.G., and J. Quiggin. "Decomposing Input Adjustments Under Price and Production Uncertainty." *American Journal of Agricultural Economics* 83(February 2001):20-34.

Coulibaly, N., and B.W. Brorsen. "Monte Carlo Sampling Approach to Testing Nonnested Hypotheses: Monte Carlo Results." *Econometric Reviews* 18 2(1999):195-209.

Christainsen, S., T. Svejcar, and W.A. Phillips. "Spring and Fall Cattle Grazing Effects on Components and Total Grain Yield of Winter Wheat." *Agronomy Journal* 81(1989):145-150.

Dameus, A., F. G-C. Richter, B.W. Brorsen, and K.P. Sukhdial. "AIDS versus Rotterdam: A Cox Nonnested Test with Parametric Bootstrap." *Journal of Agricultural and Resource Economics* 27(December 2002):335-347.

Davidson, R., and J.G. MacKinnon. "Several Tests for Model Specification in the Presence of Alternative Hypotheses." *Econometrica* 49(May 1981):781-793.

Frank, M.D., B.R. Beattie, and M.E. Embleton. "A Comparison of Alternative Crop Response Models." *American Journal of Agricultural Economics* 72(August 1990):597-603.

Hart, R.H., M.J. Samuel, P.S. Test, and M.A. Smith. "Cattle, Vegetation, and Economic Responses to Grazing Systems and Grazing Pressure." *Journal of Range Management* 41(1988a):282-286.

Horn, G.W., M.D. Cravey, F.T. McCollum, C.A. Strasia, E.G. Krenzer, Jr., and P.L. Claypool. "Influence of High-Starch vs High-Fiber Energy Supplements on Performance of Stocker Cattle Grazing Wheat Pasture and Subsequent Feedlot Performance." *Journal of Animal Science* 73(1995):45-54.

Isik, M."Resource Management under Production and Output Price Uncertainty: Implications for Environmental Policy." *American Journal of Agricultural Economics* 84(August 2002):557-571.

Kaitibie, S., F.M. Epplin, B.W. Brorsen, G.W. Horn, E.G. Krenzer, Jr., and S.I. Paisley. "Optimal Stocking Density for Dual-Purpose Winter Wheat Production." *Journal of Agricultural and Applied Economics* 35(April 2003):29-38.

King, R.P., and G.E. Oamek. "Risk Management by Colorado Dryland Wheat Farmers and the Elimination of the Disaster Assistance Program." *American Journal of Agricultural Economics* 65(May 1983):247-255.

Maddala, G.S., and F.D. Nelson. "Maximum Likelihood Methods for Models of Markets in Disequilibrium." *Econometrica* 42(November 1974):1013-1030.

Paris, Q. "The von Liebig Hypothesis." *American Journal of Agricultural Economics* 74(November 1992):1019-1028.

Paris, Q., and K. Knapp. "Estimation of von Liebig Response Functions." *American Journal of Agricultural Economics* 71(February 1989):178-186.

Pesaran, H., and A. Deaton. "Testing Nonnested Nonlinear Regression Models." *Econometrica* 46(May 1978):677-694.

Pesaran, M. H., and B. Pesaran. "A Simulation Approach to the Problem of Computing Cox's Statistic for Testing Nonnested Models." *Journal of Econometrics* 57(1993):377-392.

Pinchak, W.E., W.D. Worrall, S.P. Caldwell, L.J. Hunt, N.J. Worrall, and M. Conoly. "Interrelationships of Forage and Steer Growth Dynamics on Wheat Pasture." *Journal of Range Management* 49(March 1996):126-130.

Redmon, L.A., E.G. Krenzer, Jr., D.J. Bernardo and G.W. Horn, "Effect of Wheat Morphological Stage at Grazing Termination on Economic Return." *Agronomy Journal* 88(1996):94-97.

Redmon, L.A., F.T. McCollum, III., G.W. Horn, M.D. Cravey, S.A. Gunter, P.A. Beck, J.M. Mieres, and R. San Julian. "Forage Intake by Beef Steers Grazing Winter

Wheat with Varied Herbage Allowances." *Journal of Range Management* 48(May 1995):198-201.

Tembo, G., B.W. Brorsen, and F.M. Epplin. "Stochastic Linear Response Plateau Functions." Unpublished. Stillwater: Oklahoma State University.

Torell, L.A., K.S. Lyon, and E.B. Godfrey. "Long-Run versus Short-Run Planning Horizons and the Rangeland Stocking Rate Decision." *American Journal of Agricultural Economics* 73(August 1991): 795-806.

True, R.R, F.M. Epplin, E.G. Krenzer, Jr., and G.W. Horn. A Survey of Wheat Production and Wheat Forage Use Practices in Oklahoma. Oklahoma Agricultural Experiment Station Bulletin B-815, 2001

Table 1. Average Daily Gain Response to Forage Allowance for Switching Regression Model and Linear Response Stochastic Plateau Function

Regressor	Two-Regime Switching Regression	Linear Response Stochastic Plateau
Intercept	0.5001	0.4812
	(0.1234)	(0.1038)
Forage allowance	50.5474	66.4665
	(12.4740)	(9.59)
Plateau gain	1.0621	1.1798
	(0.0145)	(0.0997)
Forage allowance at		0.0105
maximum gain		(0.0011)
Variance of year random		0.0384
effects		(0.0214)
Variance of error term	0.0778	0.0123
	(0.0209)	(0.0021)
Variance of plateau level	0.0045	0.0022
gain	(0.0018)	(0.0163)
log likelihood	21.1	46.15

Table 2. Cox Parametric Bootstrap Test Statistics for von Liebig Functions with Average Daily Gain as a Function of Forage Allowance

Test Statistic	Data	Estimated Model	Test Values
Log Likelihood Value (LLV)	Actual Data	Linear Response Stochastic Plateau (LRSP)	46.15
Log Likelihood Value (LLV)	Actual Data	Switching Regression (SR)	21.1
Difference			25.05
Average LLV	H_0:LRSP	LRSP	10.70
Average LLV	H_0:LRSP	SR	14.91
Difference			-4.21
Average LLV	H_0:SR	LRSP	19.15
Average LLV	H_0:SR	SR	30.1
Difference			-10.95
p-Value		H_0:LRSP	1.000
p-Value		H_0:SR	0.048
Test Result			Reject SR

Table 3. Optimal Stocking Density under Production and Output Price Uncertainty and Expected Cost of non-Optimal Stocking

Value of gain ($ per kg)	Optimal grazing pressure (steer-days per hectare)		Optimal stocking density (steers per hectare) [a]		
	Risk averse farmer (ϕ = 0.00005)	Risk neutral farmer	Risk averse farmer (ϕ = 0.00005)	Risk neutral farmer	Profit under risk aversion ($/ha)
	94.3210		0.7860		250.19
1.36	104.3210[b]	104.4500	0.8693	0.8704	258.20
	114.3210		0.9527		261.72

[a] Optimal stocking density is based on a 120-day grazing pressure and an initial standing forage of 1,732 kg per hectare; calculated by dividing optimal grazing pressure by 120.

[b]This row constitutes values of grazing pressure and stocking density under optimal conditions.

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Title: Optimal Grazing Pressure under Output Price and Production Uncertainty with Alternative Functional Forms
Subject:
Author: Preferred Customer
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