Heteroscedasticity and Estimation of Agricultural Debt

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Selected Poster prepared for presentation at the Agricultural & Applied Economics Association's 2014 AAEA Annual Meeting, Minneapolis, MN, July 27-29, 2014.

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1. Introduction

There are two purposes for this research:

1) Test for heteroscedasticity: Is there any evidence that this risk changes over time?
2) Examine the effect of increases in risk on agricultural debt

2. Risk Balancing Theory

The basic concept follows from Collins [1]

$$\delta^*(t) = 1 - \frac{\rho {\sigma_A}^2(t)}{[\mu_A(t) - K(t)]} \qquad (1)$$

where δ^* is the optimal debt to asset ratio, ρ is the producer's absolute risk aversion, $\mu_A(t)$ is the expected rate of return on agricultural assets, $K(t)$ is the cost of debt, and ${\sigma_A}^2(t)$ is the variance of the rate of return on agricultural assets.

In this study, we multiply the equation through by the level of agricultural assets to obtain

$$D^*(t) = A(t) - \frac{\rho {\sigma_A}^2(t)}{[R_A(t) - K(t)A(t)]} \qquad (2)$$

where is $D^*(t)$ is the level of agricultural debt, $A(t)$ is the level of agricultural asset, ${\sigma_A}^2(t)$ is the variance of return on agricultural assets, $R_A(t)$ is the level of agricultural returns, and $K(t)A(t)$ is the opportunity cost of return on agricultural assets (valued in terms of the cost of debt)

In order to scale the problem, we then divide through by the number of acres and take the first-order Taylor series expansion to yield

$$\widetilde{D}^*(\mathrm{t}) = \alpha_0 + \alpha_1 \tilde{R}_A(t) + \alpha_2 {\sigma_A}^2(t) + \alpha_3 K(\mathrm{t})\tilde{A}(t) + \epsilon(t) \qquad (3)$$

where $\widetilde{D}^*(\mathrm{t}) = D^*(t)/L(t)$ (given that $L(t)$ is the number of acres), $\tilde{R}_A(t) = R_A(\mathrm{t})/L(\mathrm{t})$, $\tilde{A}(t) = A(t)/L(t)$

In general, we expect that

- $\alpha_1 \gg 0$: increases in the expected return increase the optimal debt level
- $\alpha_2 \ll 0$: increases in the level of risk decrease the optimal debt level
- $\alpha_3 \ll 0$: increases in the opportunity cost of capital decrease the optimal debt level

3. Econometric Specification

3.1 Expected Profit

Several approaches have been used to model expected profit. For example, Moss, Shonkwiler and Ford [2] used a time series (autoregressive) formulation to model expected returns on agricultural assets.

In this study we use a linear profit function based on input and output prices

$$\tilde{\pi}(t) = \beta_0 + \beta_1 p_1(t) + \beta_2 p_2(t) + \beta_3 w_1(t) + \beta_4 w_2(t) + \beta_5 w_3(t) + v(t) \qquad (4)$$

where $\tilde{\pi}(t)$ is the profit per acre, p_1 is the price index for crops sold, p_2 is the price index for livestock sold, w_1 is the price index for seeds, w_2 is the price index for fertilizer, and w_3 is the price index for fuel (all price index are in the U.S level).

The estimated coefficients for this formulation are presented in Table 1. In general, we would expect that increases in the output prices would increase the profit per acre. However, the coefficient for crop production is negative in three states (California, Florida, and Georgia). The reason for this anomaly may be the composition of crops in each state. For example, both California and Florida produce a significant quantity of fruits and vegetables which may not be well represented in the general crop price index. The results for the livestock output are closer to our expectations with the only negative estimate in Georgia.

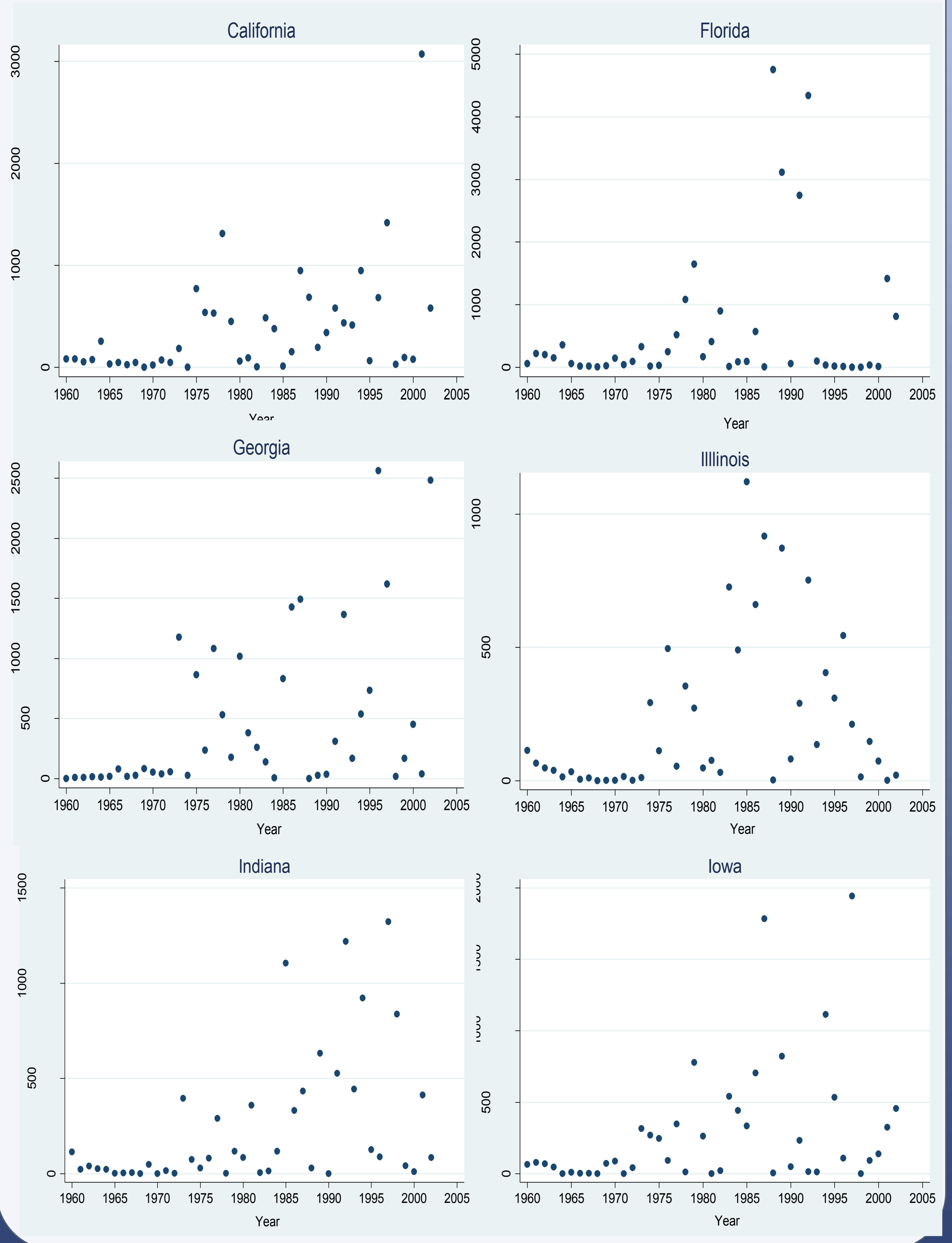
Table 1: Profit Function Estimates

	California	Florida	Georgia	Illinois	Indiana	Iowa
pcrop	-0.31264	-1.17012	-1.26545	0.52529	0.53716	0.47921
	(0.52540)	(0.64899)	(0.58981)	(0.40850)	(0.41985)	(0.45894)
plive	1.64445	1.66659	-0.05830	0.76850	0.55014	0.84700
	(0.54204)	(0.66954)	(0.60849)	(0.42144)	(0.43314)	(0.47348)
pseed	1.94605	3.27596	2.78444	-0.20646	-0.09205	-0.21479
	(0.37165)	(0.45907)	(0.41721)	(0.28896)	(0.29698)	(0.32464)
pfert	0.04482	-0.56415	0.86148	0.08795	0.14538	0.14629
	(0.59238)	(0.73172)	(0.66500)	(0.46057)	(0.47337)	(0.51745)
pfuel	-0.65114	-0.50793	-0.80653	-0.08631	-0.02836	0.13947
	(0.34816)	(0.43005)	(0.39084)	(0.27069)	(0.27821)	(0.30412)
const	-48.17525	-28.14763	-10.79019	-7.42728	-9.86015	-15.96324
	(13.88744)	(17.15399)	(15.58976)	(10.79745)	(11.09737)	(12.13075)

Asymptotic standard errors are in parentheses.

3.2 Test for heteroscedasticity

Graph 1: Estimated Residual Squares from Profit Function



Risks are measured by estimated residuals squares

Based on graph 1, estimated residuals squares, the measurement of risks, are not constant over time for each state. In order to prove this hypothesis, we apply the Breusch–Pagan method to test heteroscedasticity. The basis of the Breusch–Pagan approach is to test whether the estimated variance of the residuals from a regression are dependent on the values of the independent variables.

Specially, from equation (4), we begin by setting $\tilde{V}(t)=v(t)^2$

Next, we regress the estimated variance on independent variables in equation (4)

$$\tilde{V}(t) = \beta_6 + \beta_7 p_1(t) + \beta_8 p_2(t) + \beta_9 w_1(t) + \beta_{10} w_2(t) + \beta_{11} w_3(t) + \varepsilon(t) \qquad (5)$$

If an F-test confirms that the independent variables are jointly significant then the null hypothesis of homoscedasticity can be rejected.

Breusch–Pagan is also conducted based on Lagrange multiplier (LM). If the auxiliary regression is performed, LM yields the test statistic with chi-square distribution. In table 2, p-values are reported based on two methods: F-test and LM with chi-square distribution. The null hypothesis of homogeneity is rejected for four states with both the F-test and chi-square tests at the 10%. For Florida and Iowa, however, the these two tests yield the different results.

Table 2: P values of F-test and Chi-square test for Breusch–Pagan

	California	Florida	Georgia	Illinois	Indiana	Iowa
F-test	0.028	0.173	0.023	0.089	0.045	0.138
Chi-square	0.003	0.013	0.005	0.007	0.002	0.008
Ho: Homogeneity	rejected	mixed	rejected	rejected	rejected	mixed

Risks are estimated by Loess estimator

There are other different approaches used to estimate the risk. For example, Moss, Shonkwiler and Ford [2] used an Autoregressive Conditional Heteroscedasticity (ARCH). In this study, we also apply Loess estimator to estimate risks.

Specifically, we model this variance using a locally linear leas squares to

$$\min \sum_{S=1}^{T} k(t,s)(\tilde{V}(s) - \gamma_0(\mathrm{t}) - \gamma_1(t)s)^2 \qquad (6)$$

where $k(t,s)$ is a kernel which decreases as t and s diverge

Using the estimated coefficients(i.e., $\hat{\gamma}_0$ and $\hat{\gamma}_1$) from Equation 6, we can compute an variance estimate for each point in time $\hat{V}(\mathrm{t})$

$$\hat{V}(\mathrm{t}) = \sum_{S=1}^{T} k(t,s)[\gamma_0(t) + \gamma_1(t)s] \qquad (7)$$

The implied variances presented in Figure 1 indicate that the relative risk in agriculture was relatively small throughout the 1960s through about 1975 for all states. Figure 2 presents the variance and Loess estimator for Florida. In general, the risk increased in the 1970s (probably due to the citrus freezes) to a maximum in 1985 and then declined throughout the rest of the sample. These results contrast somewhat with the results from Illinois presented in Figure 3. Figure 4 presents the estimated variance for the sample of states

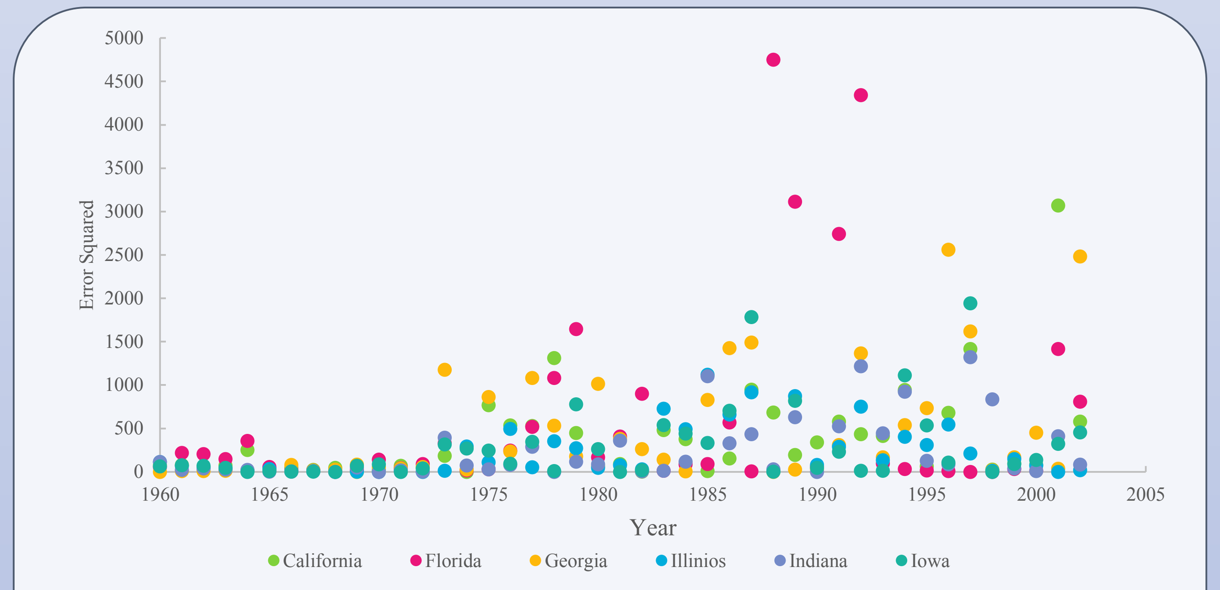


Figure 1:*Estimated Residuals Squared*

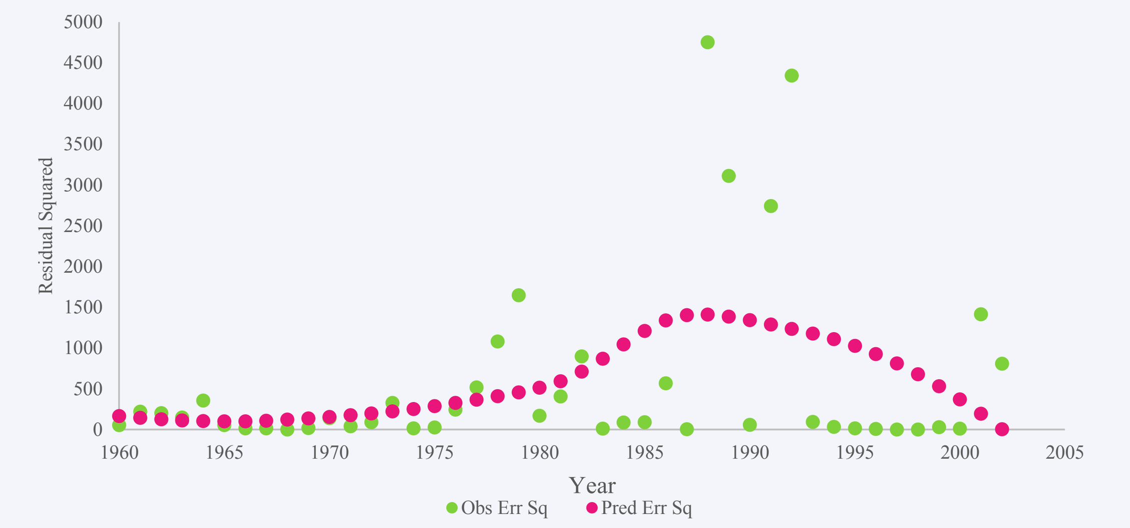


Figure 2:*Loess Estimate of Variance for Florida*

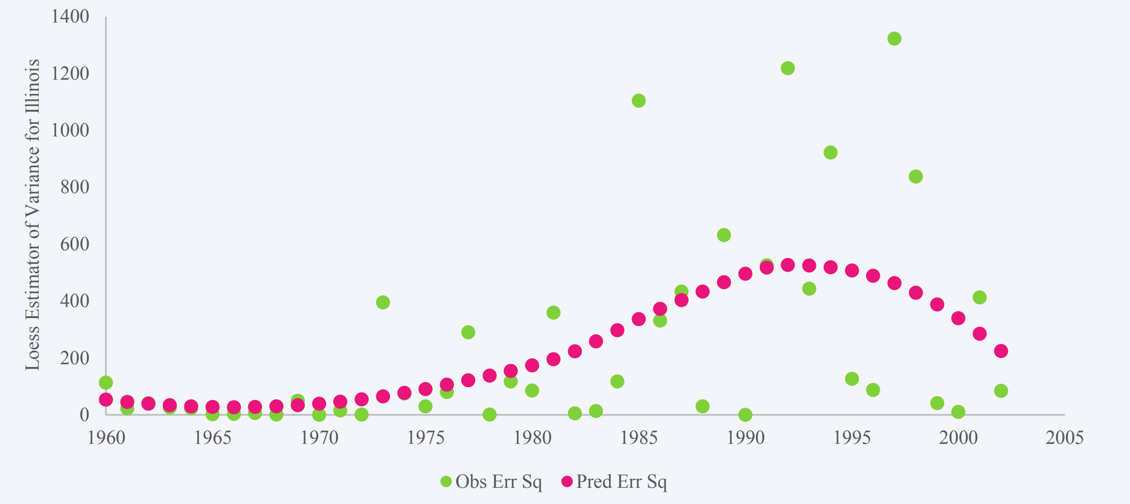


Figure 3:*Loess Estimate of Variance for Illinois*

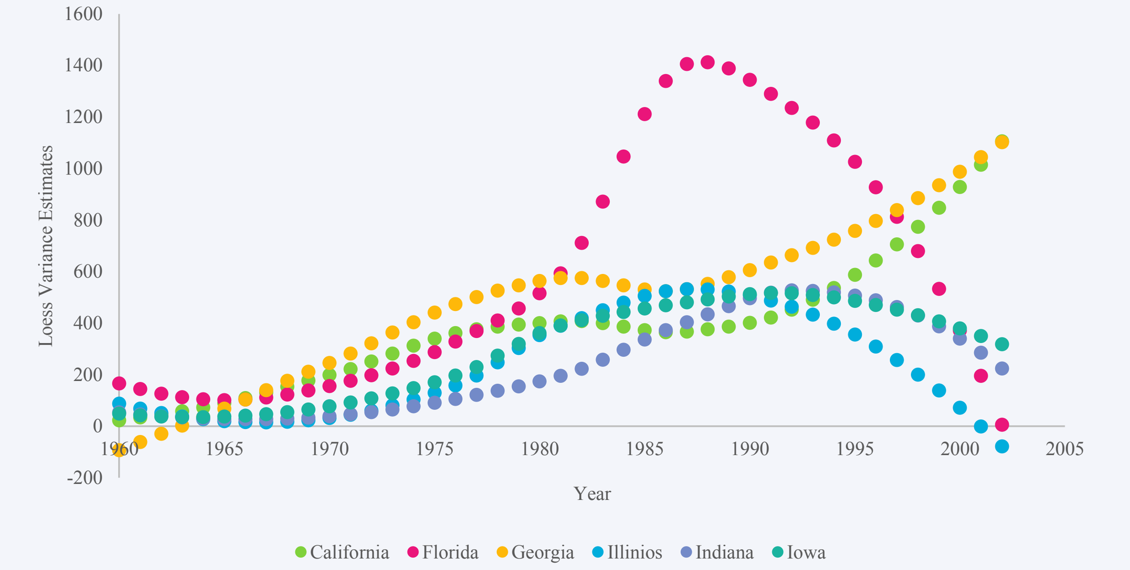


Figure 4:*Loess Estimates of Variance*

4. Risk Balancing Results

The optimal debt equation is structured by the Error Correction Model

$$\Delta \mathrm{D}^*(\mathrm{t}) = \alpha_0 + \alpha_1 \tilde{R}_A(t-1) + \alpha_2 {\sigma_A}^2(t-1) + \alpha_3 K(\mathrm{t}-1)\tilde{A}(t-1) + \epsilon(t) \qquad (8)$$

where $\Delta \mathrm{D}^*(\mathrm{t})$ is the first-differenced optimal debt, and all independent variables are lagged values.

The results of the risk-balancing model are presented in Table 3.

- Among four states with negative coefficient of predicted variance (estimated risks), three states are significant at 10% (i.e., Illinois, Indiana and Iowa).
- Consistent with our expectations, for every state, increases in interests paid lead to increase the opportunity costs of capital, which in turn reduce farmers' incentives to borrow debts. But this negative relationship is not strong, since only California and Indiana are significant at 10%.
- Further, the coefficients for the expected income (or profit per acre) are only positive in three states (Illinois, Indiana and Iowa). The negative coefficient, however, are not significant at 10% . 5% of significances for Illinois and Iowa suggest the strong positive relationship between expected income and optimal debt in these two states.
- Interestingly, the results for Illinois, Indiana, and Iowa are closer than other three states. It suggests that these three states are more likely to share same factors affecting their optimal debt level.
- States with unexpected signs in debt equation also have unexpected coefficients in profit function. Again, this problem may result from the fact that some states are not well represented by U.S price index. The access to state level data will be the challenge and potential improvement for this research.

Table 3: Effect of Estimated Variance on Debt

	California	Florida	Georgia	Illinois	Indiana	Iowa
pred variance	0.0002	-0.0005	0.0002	-0.0131***	-0.0132*	-0.0086*
	(0.0009)	(0.0009)	(0.0046)	(0.0044)	(0.0068)	(0.0050)
exp income	-0.0033	-0.0292	-0.1052	0.2784***	0.2982**	0.0979
	(0.0289)	(0.0511)	(0.0855)	(0.0940)	(0.1298)	(0.1664)
interest paid	-0.0398**	-0.0555	-0.1044	-0.0439	-0.0945*	-0.0441
	(0.0164)	(0.0426)	(0.0822)	(0.0359)	(0.0536)	(0.0602)
constant	13.2199*	32.7995***	39.6367**	-27.2254	-21.7400	2.3271
	(6.5524)	(11.7432)	(15.7071)	(16.9424)	(23.8562)	(33.0379)

Note: *** significance at 0.01; ** significance at 0.05; * significance at 0.10

Reference

[1]R. A. Collins. Expected utility, debt-equity structure, and risk balancing. American Journal of Agricultural Economics, 65(3):627–629, 1985.

[2]C. B. Moss, J. S. Shonkwiler, and S. A. Ford. A risk endogenous model of aggregate agricultural debt. Agricultural Finance Review, 50:73–79, 1990.