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by

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This paper advances Williams and Thompson (1984) by updating their work and by explicitly accounting for price and yield risk in the analysis of acreage response in Brazil for soybeans and by assessing model specification. Empirical equations were estimated using seemingly unrelated regression (SUR). The robustness of the model was evaluated in the battery of misspecification tests suggested by McGuirk et al. (1993) and McGuirk et al. (1995). The results of the testing procedure suggest that the model is fairly robust in terms of normality, heteroscedasticity and functional form. The results point to parameter instability in the soybean model. The approach to the problem of parameter instability involved dividing the data in two periods and estimating regressions for each period. The signs of the significant coefficients were consistent with expectation, particularly for the second period. Soybean acreage is explained mainly by past acreage, expected prices of soybeans and land competing crops (cotton, rice, and corn), and price and yield risk. Results suggest that market signals played a reduced role in the soybean acreage growth in early years. In contrast, in recent years producers in Brazil became more sensitive to changes in prices and risk. Measures of short-run price elasticity of soybean acreage response are similar to the one obtained by William and Thompson (1984) for soybean supply. Long-run elasticities are significantly smaller.

Key words: misspecification tests, seemingly unrelated regression, soybean acreage

Introduction

Acreage response has been extensively studied in the last years. Nonetheless, the emergence of South American countries as important international suppliers of soybeans, in particular Brazil, calls for a better understanding of the factors affecting supply of this crop in Brazil.

To our knowledge, no attempt was made to estimate acreage (or supply) response in Brazil since Williams and Thompson (1984). However, since 1984 soybean acreage has increased by 128.7 percent in Brazil, allowing it to become the second largest producer of soybeans. Williams and Thompson (1984) estimated a supply function for soybeans in Brazil using a log-linear function where soybean production is explained by lagged prices of soybeans, price of wheat, acreage planted to coffee, lagged production and a dummy variable to capture the effects of a drought in 1978. These explanatory variables are intuitively sound for the period of analysis. Their major objective was to evaluate the impact of government intervention in the Brazilian exports in the 1960's and 1970's. The model developed by these authors does not appear to perform satisfactorily as most of the coefficients presented in the final model are statistically insignificant.

Here, we estimated acreage response in the Brazilian agriculture using annual observations from 1976 to 2003 obtained from the Brazilian Ministry of Agriculture[1]. We advance Williams and Thompson (1984) by updating, explicitly accounting for price and yield risk, by assessing model specification, and by estimating empirical equations using seemingly unrelated regression (SUR). Ordinary least square (OLS) regressions are also estimated for

[1] Same results were obtained using USDA data, available for production, acreage and yield.

soybeans in order to avoid difficulties posed by the apparent structural change. The empirical model consists of four acreage equations (soybeans, cotton, corn and rice). We assume that these are land-competing crops and, therefore, the allocation of land is determined jointly.

The need to include risk in this type of analysis was previously stressed in the literature (for example Just (1975), Thompson and Abbott (1982), and later by Holt and Chavas (2002), among many others). Risk is frequently addressed in the literature in terms of both price and production risk and also in terms of the impact of government programs on the underling risk structure.

In the conceptual model, soybean acreage is assumed to be a function of expected price of soybeans, price of land-competing crops (cotton, corn and rice), lagged acreage of soybeans, price and yield risk of soybeans, and the resources spent by the Brazilian Government in agriculture support programs[2]. Risk is estimated based on the variability of the season average farm price as measured by the squared deviation from a three-year moving average.

Review of Literature

Houck and Ryan (1972) suggested that planted acreage should be viewed as a function of expected market conditions, government programs, and other exogenous variables. Expected market conditions are typically expected own prices and prices of competing crops deflated by cost of production. Among other exogenous variables, proxies for risk and lagged acreage are also commonly included (Park and Garcia 1994).

Price expectation is an important component of acreage response models, given the underlying uncertainty associated with the biological lags in agricultural production. Ferris (1998) describes some alternatives to estimate expected prices. Naive expectations utilize the price in the most recent period as a proxy for expected price. The distributed lag approach consists in including other lags of prices in generating expectations. The problem with this method resides in the fact that it is not clear how many lags should be included in the model. Ferris suggests that the appropriate lag structure may be found by introducing additional lagged P_{t-i} until the coefficients are not significant or turn negative. Nonetheless, the remedy proposed by Ferris can be potentially worse than the illness, since the side effects of this process are the introduction of multicollinearity and the loss of degrees of freedom, and depending on how it is done it can also create a generated regressor problem.

Alternatively, price expectations can be estimated using the rational expectations model. This approach assumes that decision makers are able to formulate their beliefs about the future, taking all relevant information into consideration. This method is quite unrealistic in our context

[2] Price and government expenditures were deflated using the consumer price index. Two steps were taken in order to obtain real prices and amount invested: first nominal values in several currencies adopted in Brazil in the period considered were converted to a common currency (Real, symbolized by R$), and in a second step nominal values in the common currency were deflated using the consumer price index. Deflation was performed to avoid the problems caused by the existence of several currencies and extreme high inflation rates observed in Brazil. The choice of the consumer price index as a deflator is of less importance given that deflators in Brazil for this period are highly correlated.

since it assumes, among other things, that decision makers have comprehensive information and that they know how to effectively use the information they have. Although the literature suggests a large array of methods to estimate expected prices, it seems reasonable that the researcher should resort to these models only when a theoretical base and/or a priory information is not readily available. In this study we follow Shideed and White (1989) in using lagged cash prices as price expectations different crops. Different models are tested in order to determine which structure best forecast prices using past prices.

Different strategies have been proposed in the literature to incorporate risk in the estimation of both supply and acreage response functions. These strategies vary from the simple incorporation of standard deviations of price and yield in past periods (Sadoulet and Janvry 1995), difference between actual prices and expected prices (Just, 1975), to more sophisticated methods using GARCH procedures (Holt and Aradhyula 1990). In this study we follow Park and Garcia (1994) by employing a proxy for risk based on the variability of the season average farm price as measured by the squared deviation from a three-year moving average. This measure of risk has the interesting feature of aggregating in one measure price risk and yield risk.

Methods

Expected Prices

Three alternatives to estimate expected prices are assessed: Naive expectation model, moving average model, and autoregressive model. The models tested are:

Naive expectations model:

$$P_t = P_{t-1}$$

Moving average:

$$P_t = \beta\left(\frac{1}{N}\sum_{n=1}^{N} P_{t-n}\right) + u_t\,,\ N = 1, 2, 3, 4.$$

Autoregressive models

$$P_t = \sum_{i=1}^{I} \delta_i P_{t-i} + u_t\,,\ \ I = 1, 2, 3, 4.$$

The diversity of methods proposed to estimate expected prices creates the question of how we are to compare the adequacy of these models to the data available. One way to evaluate the model is using the Bayesian Information Criterion (BIC). Models more adequate will have lower values of BIC. Another way is to compare forecasts is through the use of Theil's U statistics. Although no consensus exists regarding the usefulness of these statistics, the following form referred to as U_2 has useful interpretation:

(1) $$U_2 = \frac{\sqrt{\frac{1}{n-1}\sum_{i=2}^{n}\left[\left(Y_t^s - Y_{t-1}^a\right) - \left(Y_t^a - Y_{t-1}^a\right)\right]^2}}{\sqrt{\frac{1}{n-1}\sum_{i=2}^{n}\left(Y_t^a - Y_{t-1}^a\right)^2}}, \quad 0 \le U_2 \le \infty$$

where Y^s and Y^a are the simulated and the actual values of Y_t respectively. Note that if we have perfect forecast, that is $\left(Y_t^s\right) = \left(Y_t^a\right)$, U_2 will be zero. Note also that when we have naive expected prices, the numerator and the dominator in (1) are identical, and therefore $U_2 = 1$. This implies that any forecast between zero and one is better than the naive model.

Risk

Here we adapt the method used by Park and Garcia (1994) to incorporate price and yield risk. Price risk is based on the variability of the season average farm price as measured by the squared deviation from a three-year moving average. We can also incorporate yield variability into the measure of risk as follows:

$Risk_t = \frac{\left(R_{t-1} - MA_t\right)^2}{MA_t}$, where $MA_t = \left(R_{t-2} + R_{t-3} + R_{t-4}\right)/3$, and R_t is the season average price received by farmers in year t times the average yield in the same year. One may argue that this method is flawed since departures of revenue from the average are treated equally, that is, there is no distinction between gain and loss to the farmer. Obviously, in the farmer's perspective, situations where $\left(R_{t-1} - MA_t\right) > 0$ are desirable and situations where $\left(R_{t-1} - MA_t\right) < 0$ are undesirable. Thus, since a risk-averse agent would prefer $\left(R_{t-1} - MA_t\right) > 0$ over $\left(R_{t-1} - MA_t\right) \le 0$, the method used by Park and Garcia (1994) may not completely capture the risk perceived by farmers, especially if yield-boosting technologies are introduced over time. We tried to improve the model by adapting the risk measure such that

$$Risk_t = \begin{cases} \frac{\left(R_{t-1} - MA_t\right)^2}{MA_t} & if \quad \left(R_{t-1} - MA_t\right) \le 0 \\ 0 & if \quad \left(R_{t-1} - MA_t\right) > 0 \end{cases}$$

The economic model

Equations (2) through (5) represent the acreage response functions for soybeans (2), rice (3), corn (4), and cotton (5). For instance, equation (2) indicates that the soybean acreage (AS_t) depends on own expected price and the expected price of land-competing crops, and government expenditures in agricultural support programs (GOV). Table 1 presents the definition of the variables used in equations (2) to (5).

(2) $$\ln AS_t = \alpha_1 + \alpha_2 \ln PS_t^E + \alpha_3 \ln PCT_t^E + \alpha_4 \ln PR_t^E + \alpha_5 \ln PC_t^E + \alpha_6 \ln GOV_t + \\ + \alpha_7 RISKS_t + \alpha_8 \ln AS_{t-1} + u_{so,t}$$

(3) $\ln AR_t = \beta_1 + \beta_2 \ln PR_t^E + \beta_3 \ln PCT_t^E + \beta_4 \ln PC_t^E + \beta_5 \ln PS_t^E + \beta_6 \ln GOV_t + $
$$+ \beta_7 RISKR_t + \beta_8 \ln AR_{t-1} + u_{rc,t}$$

(4) $\ln AC_t = \delta_1 + \delta_2 \ln PC_t^E + \delta_3 \ln PCT_t^E + \delta_4 \ln PR_t^E + \delta_5 \ln PS_t^E + \delta_6 \ln GOV_t + $
$$+ \delta_7 RISKC_t + \delta_8 \ln AC_{t-1} + u_{c,t}$$

(5) $\ln ACT_t = \gamma_1 + \gamma_2 \ln PCT_t^E + \gamma_3 \ln PC_t^E + \gamma_4 \ln PR_t^E + \gamma_5 \ln PS_t^E + \gamma_6 \ln GOV_t + $
$$+ \gamma_7 RISKCT_t + \gamma_8 \ln ACT_{t-1} + u_{ct,t}$$

The expected signs of the estimated coefficients are derived from simple economic logic. An increase in soybeans own price is expected to have a positive impact in soybean acreage, increases in the price of land-competing crops are expected to have a negative impact on soybean acreage. Also, government expenditures are expected to reduce acreage of soybeans since most of the government support programs benefited land-competing crops proportionally more.

Model validation

The credibility of the conclusions is built on efforts employed to construct a well specified model, avoiding biased and inconsistent estimation. In this line, McGuirk et al. (1993) and McGuirk et al. (1995) present a consistent strategy to test for model misspecification. Many misspecification tests have been proposed in the literature, but the difficulty in using isolated tests resides in the fact that a test is valid only when no other source of misspecification exists. McGuirk et al suggest a framework where a comprehensive set of individual and joint misspecification tests (for individual equations and for the system as a whole) can help identify misspecification sources and guide re-specification efforts. We perform the tests for the system and for the soybean equation. Individual and joint misspecification tests proposed by McGuirk et al are described in table 2.

Results

The results presented here focus on the estimation of the soybean equation. The first step towards the estimation of the system of equations consists in verifying the stationarity of the time series used. Table 3 suggests that the majority of the series are non-stationary in level (excluding logarithm of rice acreage (*lnar*), risk of cotton, rice, and soybeans). In general, the series become stationary in the first difference, except the logarithm of cotton, rice, and soybean prices. These series become stationary when differenced twice. Given the heterogeneity in the order of integration of the series, it seemed more adequate to estimate the models with variables in the first difference in order to avoid over-differencing some of the series.

The next step consists in calculating expected prices that will be used in the regressions. Three alternatives to estimate expected prices were assessed: naive expectation model, moving average model, and autoregressive model. The criterion used to select the models was the

Bayesian Information Criterion (BIC), which yields more parsimonious models. Results are found in table 4.

Table 4 suggests that none of the models selected by the BIC criterion forecasts better than the naive model. This is possibly explained by the fact that the crops included in this study are annual crops and it is not clear that there is a cyclical behavior in the price formation. Thus, there is no apparent reason to believe that the information contained for prices in years beyond t-1 can help forecast prices. This problem could be potentially overcome by using futures markets as a proxy for expected prices. However, such information is not available since most agricultural futures contracts in Brazil suffer from lack of sufficient liquidity. Hence, in this study we choose to use naive expectations in the regressions.

Table 5 presents the results of the seemingly unrelated regression for soybeans. The overall fit of the model is satisfactory ($R^2 = 0.80$) and the signs of the significant coefficients are consistent with expectations. Table 5 suggests that soybean acreage is explained by expected prices of soybeans, rice, and corn, and lagged soybean acreage. Soybean expected price has a significant impact on current acreage, whereas the price of land-competing crops has a negative impact on soybean acreage. The validity of these results depends on the robustness of the model. Table 6 presents the results of the testing strategy suggested by McGuirk et al (1995). We present results for the whole system and for the soybean equation.

The results for the whole system are quite satisfactory, with only the Chow test significant at the 1% level. The hypothesis of normality is not rejected, heteroscedasticity, both static and dynamic, does not seem to be of concern. Also, the results of the RESET2 test for functional form suggest that the log-linear functional form adopted by Williams and Thompson (1984) is adequate for modeling soybean acreage response in Brazil.

The results for the soybean equation suggest that the null hypothesis of stable parameters in the Chow test is rejected. This rejection is consistent with the fact that the Brazilian government strongly intervened in the soybean market in the 60's and 70's, (which motivated the work of Williams and Thompson 1984) and much less intervention was observed in recent periods, which caused the change in the market dynamics, with producers becoming more sensitive to market signals in recent years. The problem of parameter instability will be approached by dividing the data in two periods and by estimating soybean regressions for these two periods.

Since the soybean market is the one we are interested in, we estimate two sets of equations using OLS. In the first set we use variables in level and in the second the first difference is used. This approach is used so that it is possible to compare the results of this research with the results obtained by Williams and Thompson (1984), especially because these authors used data in level in the analysis. Naturally, we also present results using variables in the first difference, since most of the variables are stationary only in the first difference. Results are presented in tables 7 and 8.

Some important insights can be gained by comparing tables 7 and 8 with Williams and Thompson (1984) results. Using data from 1960 to 1978, Williams and Thompson (1984) estimated the following supply response function:

$$\text{(6)} \quad \log SSB = \underset{(0.94)}{5.96} + \underset{(1.01)}{0.53} \log PSB_{t-1} - \underset{(-1.67)}{0.98} \log PWT_{t-1} - \underset{(-0.64)}{0.27} \log ACB + \underset{\mathbf{(5.84)}}{0.84} \log SSB_{t-1} - \underset{(-1.11)}{0.34} DRT$$

where *SSB* is the supply of soybeans, *PWT* is the price of wheat, *ACB* is acreage of coffee and *DRT* is a dummy variable to account for the drought in 1978. The values in parenthesis are t-values and R^2 is 0.981. Apparently, the first lag of soybean supply is the only coefficient that is statistically significant. The short-run price elasticity of soybean supply is 0.53, whereas the long-run price elasticity of soybean supply is 3.45. Naturally, these elasticities must be interpreted with caution since the own price elasticity depends on a coefficient that is not statistically different from zero.

In terms of statistical significance, these results are similar to the results shown in table 7, panel a, table 8, panel a. Many of the coefficients are not significant. These panels suggest that the expansion of soybean acreage in the period of 1960-1968 (Williams and Thompson 1984) continuing through 1988, was not largely driven by market signals, and cannot be satisfactorily explained by the variables included. On the other hand, table 7, panel b, and table 8, panel b present a very different picture. In recent years, producers are much more sensitive to market signals, that is, changes in soybean prices, prices of land competing crops, and risk are important factors influencing decisions on soybean acreage in Brazil.

The elasticities presented in table 8, panel b, are consistent with the limited intervention of the Brazilian government in the soybean market in recent years. The short-run own price elasticity is estimated in 0.47 and the long-run own price elasticity is 1.02. Cross price elasticities are significant, and the signs of the coefficients are consistent with expectation. Increase in the expected prices of cotton, rice, corn, and price and yield risk tend to reduce acreage planted to soybeans.

Conclusions

This paper advances Williams and Thompson (1984) by updating their work and by explicitly accounting for risk in the analysis of acreage response in Brazil for soybeans. Empirical equations were estimated using seemingly unrelated regression (SUR). The robustness of the model was evaluated in a battery of misspecification tests as suggested by McGuirk et al. (1993) and McGuirk et al. (1995).

The results of the testing procedure proposed by McGuirk et al. suggest that the model estimated is fairly robust in terms of normality, heteroscedasticity and functional form. Parameter instability (in terms of variance) led us to divide data in two periods (1976-1988 and 1989-2003). The signs of the significant coefficients were consistent with expectations, particularly during the last period. Short-run and long-run acreage elasticities seem reasonable and differ somewhat from those estimated by William and Thompson (1984). Differences may be related to the specification of the acreage versus production response and to changes in the economic environment. Regardless, it seems clear that Brazilian producers respond actively to changes in market signals. This implies that if prices of soybeans continue favorable compared to other crops, it is likely that acreage of soybeans continue to increase, either by substituting other crops or by the addition of new land to the production system.

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Table 1. Definition of Variables

Variable Name	Definition
AS	Soybean acreage (harvested), 1000 ha
AR	Rice acreage (harvested), 1000 ha
AC	Corn acreage (harvested), 1000 ha
ACT	Cotton acreage (harvested), 1000 ha
PS^E	Expected price of soybeans, R$ per ton
PCT^E	Expected price of cotton, R$ per ton
PR^E	Expected price of rice, R$ per ton
PC^E	Expected price of corn, R$ per ton
GOV	Total government expenditures in support programs, million (R$), deflated by the Consumer Price Index
RISKS	Price/yield risk for soybeans
RISKR	Price/yield risk for rice
RISKC	Price/yield risk for corn
RISKCT	Price/yield risk for cotton

Table 2. Individual and Joint Misspecification Tests

Aspect tested	Test
Individual misspecification tests	
Normality	Doornik and Hansen, omnibus test
Functional form	RESET2 test
Static heteroscedasticity	White test
Dynamic heteroscedasticity	ARCH test
Parameter stability	Rao test (adjusted for small sample)
Independence (no autocorrelation in the errors)	Breusch-Godfrey test
Joint misspecification tests	
Simultaneously asses stability of parameters, functional form, and independence	Conditional mean
Dynamic and static heteroscedasticity and stability of variance	Conditional variance

Table 3. Results of the Dickey-Fuller Test in Level and First Difference.

Variable	Model*	# lags	Test Statistic	1% CV	5% CV	10% CV	Stationary?
			Level				
lnact	CT	7	-2.72	-4.38	-3.60	-3.24	N
lnar	CT	1	-3.95	-4.37	-3.60	-3.24	Y
lnac	CNT	4	-2.48	-3.75	-3.00	-2.63	N
lnas	CT	7	-1.94	-4.38	-3.60	-3.24	N
lnpct	NCNT	1	-1.29	-2.66	-1.95	-1.60	N
lnpr	CT	1	-2.11	-4.37	-3.60	-3.24	N
lnpc	CT	1	-1.96	-4.37	-3.60	-3.24	N
lnps	CNT	7	-2.15	-3.75	-3.00	-2.63	N
lngov	CT	1	-0.71	-2.66	-1.95	-1.60	N
RISKCT	NCNT	1	-2.33	-2.66	-1.95	-1.60	Y
RISKR	NCNT	1	-2.74	-2.66	-1.95	-1.60	Y
RISKC	NCNT	7	-0.14	-2.66	-1.95	-1.60	N
RISKS	CNT	1	-3.97	-3.74	-3.00	-2.63	Y
			Difference				
Δlnact	CNT	1	-5.95	-3.75	-3.00	-2.63	Y
Δlnac	NCNT	3	-3.57	-1.95	-1.95	-1.60	Y
Δlnas	CNT	1	-6.63	-3.75	-3.00	-2.63	Y
Δlnpct	CT	7	-1.49	-3.60	-3.24	-1.60	N
Δlnpr	CT	5	-0.82	-4.38	-3.60	-3.24	N
Δlnpc	NCNT	1	-3.41	-2.66	-1.95	-1.60	Y
Δlnps	NCNT	6	-1.12	-2.66	-1.95	-1.60	N
Δlngov	NCNT	1	-4.57	-2.66	-1.95	-1.60	Y
ΔRISKC	NCNT	6	-4.84	-2.66	-1.95	-1.60	Y

*CT stands for constant and trend; CNT stands for constant and no trend; NCNT stands for no constant and no trend.

Table 4. Model Selection for Estimating Expected Prices

Crop	Model*	BIC	U_2
Soybeans	$\Delta \ln PS_t = -0.04 - 0.37 \Delta \ln PS_{t-2}$ (-0.84) (-1.70)	0.13	1.81
Cotton	$\Delta \ln PCT_t = -0.01 + 0.37\ \Delta \ln PCT_{t-3}$ (-0.48) (1.66)	0.29	1.99
Corn	$\Delta \ln PC_t = -0.04 - 0.30 \Delta \ln PC_{t-1}$ (-1.05) (-1.45)	0.82	2.07
Rice	$\Delta \ln PR_t = -0.04 - 0.22 \Delta \ln PR_{t-4}$ (-1.19) (-1.00)	0.22	3.23

* Several equations were estimated for each crop using a moving average and autoregressive models. The equation shown for each crop represent the one selected using the BIC.

Table 5. Seemingly Unrelated Regression Results.

	$\Delta \ln AS_t$ (SUR)		
	Coefficient	S.E.	p-value
$\Delta \ln PS_t^E$	**0.4216**	0.0612	0.0000
$\Delta \ln PCT_t^E$	-0.0184	0.0710	0.7960
$\Delta \ln PR_t^E$	**-0.1030**	0.0547	0.0600
$\Delta \ln PC_t^E$	**-0.1059**	0.0585	0.0700
$\Delta \ln GOV_t$	-0.0178	0.0283	0.5290
$\Delta RISKS_t$	0.0001	0.0001	0.4890
$\Delta \ln AS_{t-1}$	**0.3356**	0.0769	0.0000
Constant	**0.0273**	0.0091	0.0030

$R^2 = 0.80$

Table 6. Brazilian Acreage Response Functions: P-Values for Full-System and Soybean Equation Misspecification Tests

Item		Whole System	Soybean equation
Individual Tests			
Normality			
Omnibus		0.114	0.393
Functional form:			
RESET2		0.730	0.283
Heteroscedasticity			
Static:	WHITE	0.194	0.075
Dynamic	ARCH	0.497	0.471
Autocorrelation			
Breusch-Godfrey		0.113	0.066
Parameter stability:			
Chow		0.049	2.27e-18
Joint Tests			
Overall mean test		0.690	0.076
Overall variance test		0.533	0.144

Table 7. Soybean Regression Using Data from 1976 to 1988 (Panel a), 1989 to 2003 (Panel b), Level.

Variable	$\ln AS_t$ (1976-1988) (panel a) (Adj. $R^2 = 0.84$)				$\ln AS_t$ (1989-2003) (panel b) (Adj. $R^2 = 0.97$)			
	Coefficient	S.E.	t	P>|t|	Coefficient	S.E.	t	P>|t|
$\ln PS_t^E$	0.3781	0.1648	2.29	0.0830	0.5177	0.0787	6.5800	0.0010
$\ln PCT_t^E$	-0.2822	0.1911	-1.48	0.2140	-0.3579	0.1143	-3.1300	0.0200
$\ln PR_t^E$	-0.3306	0.1550	-2.13	0.1000	-0.1991	0.0772	-2.5800	0.0420
$\ln PC_t^E$	0.1759	0.1980	0.89	0.4240	-0.2269	0.0880	-2.5800	0.0420
$\ln GOV_t$	-0.1107	0.0493	-2.25	0.0880	0.0429	0.0563	0.7600	0.4750
$RISKS_t$	0.0001	0.0002	0.59	0.5850	-0.0006	0.0002	-2.4700	0.0480
$\ln AS_{t-1}$	0.4619	0.1700	2.72	0.0530	0.6637	0.0704	9.4200	0.0000
Constant	6.8626	2.1070	3.26	0.0310	4.5730	1.0771	4.2500	0.0050

Normality (p-value): 0.305;
Homoscedasticity (p-value): ARCH: 0.325, White: 0.956

Normality (p-value): 0.992;
Homoscedasticity (p-value): ARCH: 0.3600, White: 0.803

Table 8. Soybean Regression Using Data from 1976 to 1988 (Panel a), 1989 to 2003 (Panel b), First Difference.

Variable	$\Delta \ln AS_t$ **(1976-1988) (panel a)** (Adj. $R^2 = 0.31$)				$\Delta \ln AS_t$ **(1989-2003) (panel b)** (Adj. $R^2 = 0.97$)			
	Coefficient	S.E.	t	P>|t|	Coefficient	S.E.	t	P>|t|
$\Delta \ln PS_t^E$	0.2030	0.2414	0.8400	0.4620	0.4775	0.0387	12.3300	0.0000
$\Delta \ln PCT_t^E$	-0.1511	0.2107	-0.7200	0.5250	-0.1380	0.0660	-2.0900	0.0910
$\Delta \ln PR_t^E$	-0.2591	0.1760	-1.4700	0.2380	-0.1058	0.0348	-3.0400	0.0290
$\Delta \ln PC_t^E$	0.1216	0.1987	0.6100	0.5840	-0.1940	0.0335	-5.7900	0.0020
$\Delta \ln GOV_t$	-0.2311	0.1988	-1.1600	0.3290	0.0148	0.0196	0.7500	0.4850
$\Delta RISKS_t$	0.0002	0.0003	0.5300	0.6320	-0.0004	0.0001	-4.8600	0.0050
$\Delta \ln AS_{t-1}$	0.9055	0.8582	1.0600	0.3690	0.5333	0.0596	8.9400	0.0000
Constant	-0.0161	0.0493	-0.3300	0.7660	0.0200	0.0064	3.1400	0.0260

Normality (p-value): 0.978;
Homoscedasticity (p-value): ARCH: 0.807, White: 0.408

Normality (p-value): 0.253;
Homoscedasticity (p-value): ARCH: 0.979, White: 0.315