QUANTIFYING LONG RUN AGRICULTURAL RISKS AND EVALUATING FARMER RESPONSES TO RISK

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Notes on Modeling Regional Crop Yields

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Introduction

Choices regarding the appropriate method for measuring probability distributions of commodity prices, yields, and returns should begin with a clear understanding of the objectives of the analysis in which they will be used. Once appropriate behavioral objectives for the target population have been identified and justified, the researcher must specify the objectives of the research. Is the purpose of the study to provide normative, managerial advice to decision makers consistent with their preferences? Or is it to predict their behavior in response to policy changes or other exogenous shocks? Young (1980) has argued that objective probability distributions measured by the analyst are appropriate for normative prescriptive applications. On the other hand, subjective probability distributions elicited from the decision maker are necessary for positive or predictive applications.

The analyst must also identify the appropriate level of aggregation for the particular research problem. For example, farm level or field level variability in yields is often appropriate for farm level applications; whereas, regional or national yield variability is appropriate in modeling the impacts of yield stochasticity on aggregate supply and endogenous price determination.

Both in positive and in normative applications the analyst is left with a large number of practical methodological decisions prior to

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estimating probability distributions or distributional moments. How long a time period of data should be used? Should conditioning variables, such as weather, and productive input levels (chemicals, irrigation, etc.) be included? How should the trend component and residual variability component be estimated? Decisions on these questions should proceed directly from the nature and objectives of the study. For example, if the probability distributions or moments are intended as proxies for subjective elicitations, measurement procedures should conform with some essential psychological requirements for expectation formation.

A major purpose of the collection of regional time series for several major crops by this project has been the development of "whitened" current probability yield distributions for each of these crops by region. These yield probability distributions will be used in the aggregate USMP model to derive endogenous price probability distributions for each crop under alternative policy or other exogenous scenarios. However, a risk-neutral specification will be used in the USMP objective function. Theoretically, one might describe the process as tracing out the effects on price of stochastic shifts in the supply curves of commodities due to yield variability. In the aggregate, decision makers are presumably assumed to behave in a risk-neutral fashion. This approach assumes that the best objective portrayal of the regional crop yield probability distribution is required to accurately predict the (risk-neutral) response of market prices to yield stochasticity.

Modeling Distributions & Normalizing Data

The problem stated in the previous section can be formalized in the following way. Suppose that yields are described by a probability distribution that is conditional on some information set I_t, which changes over time:

$$Y_t \sim F(y|I_t).$$

Precisely what information is relevant is not known (or available even if known). One can also view the problem as an attempt to describe how the distribution changes over time:

$$Y_t \sim F_t(y).$$

The objective of deriving a normalized set of yields, say for period s, can be accomplished, in principle, through the transformation:

$$Y_t^* = F_s^{-1}(F_t(y_t)).$$

Obviously if $F_s = F_t \ \forall t$ then $Y_t^* = y_t \ \forall t$.

Another way to view the problem is in terms of a set of underlying parameters that determine the probability distribution and how it changes over time:

$$Y_t \sim F(y|\theta).$$

In a Bayesian framework one can obtain a predictive distribution for Y_s by first estimating a probability distribution for θ, say $g(\theta)$, and integrating out θ:

$$f^P(y) = \int f(y|\theta)g(\theta)\ d\theta.$$

Alternatively one can use a plug-in approach, first estimating θ, say by $\hat{\theta}$ and setting

$$F(y) = F(y|\hat{\theta}).$$

The most important and difficult problem involves that need to make informed guessed about which aspects of a distribution are changing and which are stable. The answer to this question is important in determining how to normalize the data. It is quite obvious from examining plots of yield data that location and scale (mean and variance) aspects of yield distributions have varied over time. It is difficult to tell whether higher order effects (skewness, kurtosis) are time varying.

It may in fact be the case that only scale effects are time varying in yields so that an appropriate normalization would be

$$Y_t^* = \frac{\mu_s}{\mu_t} Y_t.$$

If this were the case then all higher normalized moments, including the coefficient of variation, would be constant over time.

Problems in Modeling Yield

There are a number of problems that must be addressed in modeling yields. The first and most obvious problem is that there is trend (generally upward) in yields due to technological advances and increased capitalization and use of purchased inputs. This trend, however, is not necessarily linear in time and indeed, as Griliches pointed out, can be expected to be S-shaped over periods when significant new technological developments are adopted, as with the introduction of hybrid corn in the 1940s. If trend is taken to be a deterministic function of time, the question of the choice of a functional form arises. Other methods, such as moving average and stochastic trend methods can also be employed, though they have their own problems.

A second problem that is evident in corn yields is that there are significant differences in the variability of yields in different periods, with the absolute level of variability tending to rise as mean yields rise (whether a standardized measure, such as the coefficient of variation, has risen is not so clear). To properly model the current yield risk this heteroskedasticity will need to be addressed.

The overall shape of the distribution and particularly its skewness characteristics also must be considered. It is generally recognized that crop yields often exhibit considerable negative skew. Relatively infrequent drought conditions, in particular (consider 1974, 1983 and 1988), or unusual pest conditions (e.g., Southern corn blight in 1970) can cause significantly lower than average yields. Estimation methods that give equal weight to positive and negative deviations from means can lead to erroneous conclusions about the nature of risks. Also methods based on least squares will tend to be strongly influenced by large deviations, particularly if these occur near either end of the sample period (the 1988 drought, for example).

Autocorrelation can also be present, for a number of reasons. Droughts tend to have multiyear effects in areas where soil moisture is not replenished in a single year. Also, new varieties of crops and new methods of pest control will tend to have the greatest impact on yields soon after introduction, after which time pests evolve adaptations and reassert themselves.

An aggregation problem often arises as well due to mixing irrigated and nonirrigated acreage in a single crop yield figure. Not only does irrigation expansion affect expected yields but it changes the variability and the skewness aspects of the yield distribution by controlling the factor most directly responsible in determining these characteristics. While it is arguable that one should control for other factors influencing yields, such as soil types and chemical usage levels, the importance of moisture in crop development and growth gives this factor special importance.

Serial Dependence

Serial dependence in the data creates some difficult problems for the framework described above. In particular, one must decide whether one desires a probability distribution that is conditioned on recent events or a unconditional (long-run) distribution. Indeed a number of physical factors could produce serial dependence, including prolonged impacts from inadequate or excessive moisture, declining disease resistance in recently adopted crop varieties and other cyclic pattern in plant/pest interactions.

To illustrate the problem consider the following simple model:

$$Y_t = a + bt + e_t$$

with

$$e_t = \rho e_{t-1} + v_t,$$

where

$$v_t \sim \text{iid } N(0,\sigma^2).$$

In this case $E_t[Y_{t+1}]=a+b(t+1)+\rho(Y_t-a-bt)$ and $Var_t[Y_{t+1}]=\sigma^2$. On the other hand, the unconditional expectation is $E[Y_{t+1}]=a+b(t+1)$ with $Var[Y_{t+1}]=\sigma^2/(1-\rho^2)$.

For forecasting purposes it is clear that the conditional model is preferred. For studying long run impacts of policy changes it is not so clear. In a model driven by expectations, it would be appropriate to use the conditional model but if unconditional (long-run) results were desired it would be necessary to run the model with a sample of simulated initial conditions.

It should also be noted that obtaining a normalized series of yields faces similar difficulties. Suppose one defines the normalized series as

$$Y_t^* = Yt + b(s-t).$$

This series will continue to exhibit serial dependence; hence the normalization does not result in a random sample from the desired distribution (F_s).

The GLS Procedure

Two estimation procedures are examined. The first attempts to directly address the problems of time variation in mean and variance and the serial dependence problem within a framework familiar to economists. The basic model used is

$$Y_t = \beta_0 + \beta_1 t + \beta_2 t^2 + e_t$$

Furthermore

$$|e_t| = \alpha_0 + \alpha_1 E[y_t] + u_t$$

and

$$e_t = \rho e_{t-1} + v_t.$$

This models describes mean yields as varying quadratically over time. The standard deviation of yields is linear in the mean yield, an assumption that nests the hypothesis of constant coefficient of variation ($\alpha_0=0$, $\alpha_1=1$). Finally, the error terms are taken to be first order autocorrelated.

The estimation method used first computes OLS estimates of the β_i, from which estimates of e_t are formed. These, in turn, are used to estimate the α_i and ρ. GLS estimates of the β_i are then computed. This process is repeated 10 times (no convergence checks were made).

The approach used is described in the following schematic:

1. set $Y^*=Y$, $X^*=X$
2. regress Y^* on X^* to obtain $\hat{\beta}$
3. set $\hat{Y}=X\hat{\beta}$
4. set $e=Y-\hat{Y}$
5. regress $|e|$ on [1] and $\hat{Y}$ to obtain $\hat{\alpha}$
6. set $\hat{S}=[1\ \hat{Y}]\hat{\alpha}$
7. set $Y^* = Y/\hat{S}$, $X^*=X/\hat{S}$, $e^*=e/\hat{S}$
8. set $\rho = \dfrac{\sum_{t=2}^{n} e_t^* e_{t-1}^*}{\sum_{t=1}^{n} e_t^{*2}}$
9. set $Y^* = \begin{cases} Y_t^* - \rho Y_{t-1}^* & t>1 \\ (1-\rho^2)^{1/2} Y_1, & t=1 \end{cases}$
10. goto to 2

The Stochastic Trend Approach

An alternative, which concentrates on modeling the trend aspects of yields, is the stochastic trend (ST) model which can be written

$$Y_t = \mu_t + e_t$$

$$\mu_t = \mu_{t-1} + b_{t-1}$$

$$b_t = b_{t-1} + v_t$$

where $e_t \sim iid(0,\sigma^2)$, $v_t \sim iid(0,r^2\sigma^2)$. μ_t is the trend component which follows a random walk with random drift b_t. Given r the parameter of this model can be calculated using either a mixed estimation (Theil-Goldberger) or a Kalman Filter approach, while r may be estimated using maximum likelihood methods. This parameter measures the size of the shocks to the drift parameter relative to deviations from trend. Larger values of r imply that the trend will follow the data more closely (r = 0 implies linear trend).

This method has the drawback that it is somewhat less familiar to economists than the GLS approach. On the other hand there are potential benefits to be gained, especially given the model's flexibility in fitting nonlinear trends.

It is useful to point out that the estimated trend can be viewed as a weighted average of the sample data points. In general, the higher the value of r the more weight is placed on period t and nearby periods in the estimate of μ_t.

Empirical Results

The GLS and ST approaches were used to estimate trend components for 9 crops in 10 regions; all together 74 yield samples were used, after accounting for nonexisting region/crop combinations (the USMP model calls for 75 crop/regional yield combinations of which only Delta barley is missing here). Unfortunately, separate yield data series for irrigated and nonirrigated acreage were not available, as required by the USMP model.

The 9 crops and 10 regions examined were:

1. Wheat	1. Pacific
2. Rice	2. Northern Plains
3. Corn	3. North East
4. Oats	4. Lake
5. Barley	5. Corn Belt
6. Sorghum	6. Appalachian
7. Cotton	7. South East
8. Soybeans	8. Delta
9. Hay	9. Southern Plains
	10. Mountain

Estimates of OLS and GLS parameters for the sample period 1950-1989 are listed in Table 1. Overall, the GLS correction does not appear to have a substantial impact on the trend line for most crops (it should be pointed out that the GLS parameters could nonetheless be important for normalizing yields, especially the variance estimates).

The GLS approach was also used with a subsample of the data (1960-1989) in the belief that more recent data would be more directly relevant to the yield situation today. Instead there was a pronounced tendency to overfit the data and endpoints became extremely influential in determining the shape of the fitted trend curve (this is consistent with the results of Singh and Byerlee).

Even with the larger sample some of the estimates were unduly influenced by endpoints. This problem is inherent in least squares based approaches. For example, some of estimates exhibited convex trends ($\beta_2>0$), which can provide suspect results, particularly when forecasting. Trends which are concave and descending ($-\beta_1/\beta_2<176$) are also suspect from a forecasting perspective.

The alternative ST estimates are subject to their own set of problems. In particular, there was a tendency to overfitting through large estimated values of the ratio of trend variance to deviation from trend variance (these values are given in Table 2). This resulted in trend estimates that tracked the actual yield realizations more closely that is intuitively plausible (this can result for a variety of reasons, including serial dependence in the deviations from trend).

There are limits to what can be gained from statistical refinements of the type discussed above. From a practical perspective, disaggregation of the regional data between irrigated and nonirrigated crop yields would probably do more to improve the real-world usefulness of the results within the aggregate McCarl-Lambert model than any amount of statistical tinkering. Irrigation expansion in some regions might well account for convex yield trends for some crops. There are also good biological reasons to expect less yield variability for the same crop when grown under irrigated rather than dry land conditions.

The regional comparative advantages of crops also differ depending upon irrigated versus nonirrigated conditions. Furthermore, many policies or exogenous influences of interest, such as energy price increases, water reallocations (vis-a-vis the California drought, for example), and decoupling of farm program payments from selected crops, will have significant differences on dry land versus irrigated crops. These factors all favor use of a model which distinguishes irrigated and nonirrigated crop yields if the necessary disaggregated time series can be assembled.

Misspecification

It is also possible that some of the problems of overfitting using the methods discussed above are due to ways in which these methods weight observations in determining parameter estimates. Given that yield distributions typically display some negative skew, methods that treat positive and negative deviations symmetrically will have a tendency to place too much weight on the occasional large negative deviations, such as occurred for many crops/regions in 1983 and 1988. In order to explore the extent to which this problem exists the following experiment was run. A random sample of size 40 was generated according to

$$y_t = (20+t-0.0125t^2)e_t$$

(t=1,..,40), where et is standard lognormal. This provides a case in which the random variable has a quadratic trend with a (positively) skewed distribution. Also note that higher moments are not time invariant but normalized higher moments (coefficient of variation, skewness and kurtosis coefficients, etc.) are time invariant.

The parameters of the quadratic trend were fitted using both OLS and GLS in which the variance was modeled as described above (without any autoregressive parameters). It was also fit using ML in which the error component was correctly modeled but in which the trend was linear. The purpose of this simulation is to see whether trend estimates are more sensitive to specification errors concerning the mean or those concerning the shape of the distribution function.

1000 replications were performed and the trend estimates were evaluated for each of the three methods. The results of the simulation are presented in Table 3. Shown is the mean estimated trend value for periods 1, 20 and 40, and the root mean squared error (RMSE) and the mean absolute error relative to the actual expected value of y_t.

This experiment suggests that very significant gains are to be obtained from careful attention to the error distribution. The use of least squares methods may lead to relatively poor results even when the functional form for the trend is known. The problem is not due solely to the heteroskedastic nature of the (additive) errors; indeed the GLS procedure, which "corrects" for this, performed less well than the OLS procedure. It is more likely that explanation lies in the fact that least squares methods are highly sensitive to outliers, particularly those near the beginning or end of the sample.

The maximum likelihood method gave far better trend estimates even though the wrong model was used and there appears to be some bias in the estimates. The efficiency measure in the table is the MAE of the ML estimates relative to those of the other methods. OLS and GLS appear to be only about 65% as efficient as the ML method.

Conclusions

The preceding empirical analysis of regional crop yield trends clarifies several requirements of variability and trend measurement methodology: (a) It must accommodate varying trend patterns over different crops and regions. Several of the trends display distinct nonlinear patterns and the approaches in this paper accommodate this nonlinearity. (b) It must accommodate potentially nonnormal, skewed error distributions. Our analysis seems to indicate the presence of considerable nonnormality. The distributional (DIS) approach of Moss et al. is more flexible in accommodating this nonnormality. (c) It must accommodate potential heteroskedasticity in the error distributions over time. The GLS approach permits measurement of the pattern of heteroskedasticity in a manner readily suited to inflating (deflating) all empirical deviations to immediate future era levels. Making the variance a function of time would require fitting more parameters via the DIS approach. (d) It must accommodate potential autocorrelation in the error distribution over time. The GLS approach also accounts for this.

The proposed methodology must be sufficiently tractable that it can be understood and used by the large number of contributors to the S-232 project. This is important if the approach is not to end up as a largely ignored academic exercise. Our purpose should be to provide more consistency and rigor in the use of risk measurement techniques in applied agricultural economics research. By considering heteroskedasticity and autocorrelation, the approaches uses here are more rigorous than most past risk measurement exercises. Furthermore, it represents an improvement on previous studies that have used very simplistic trend functional specifications such as linear or simple unweighted moving averages (Singh and Byerlee, Anderson and Hazell). Nonetheless, there is room for improvement, particularly through the use of estimators that flexibly model distributional shape.

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Table 1. OLS and GLS Results: 1950-1989

		OLS			GLS					
C	R	β_0	β_1	β_2	β_0	β_1	β_2	α_0	α_1	ρ
1	1	41.521	0.975	0.010	41.905	0.958	0.007	-1.753	0.120	0.116
1	2	27.678	0.445	-0.016	27.446	0.429	-0.015	0.280	0.104	0.270
1	3	35.054	0.537	0.001	36.207	0.518	-0.008	-4.053	0.183	0.368
1	4	34.512	0.493	-0.007	33.494	0.568	-0.001	-4.955	0.224	0.283
1	5	37.193	0.682	-0.001	37.416	0.681	-0.003	1.895	0.032	0.028
1	6	32.759	0.588	-0.008	33.124	0.588	-0.011	-1.566	0.136	0.210
1	7	28.416	0.414	-0.010	28.677	0.413	-0.011	-2.270	0.191	-0.079
1	8	30.589	0.570	-0.000	30.661	0.570	-0.001	2.477	0.016	0.056
1	9	24.426	0.461	-0.014	24.533	0.460	-0.014	1.626	0.063	0.003
1	10	28.359	0.459	-0.005	28.286	0.460	-0.004	-0.429	0.082	-0.041
2	1	54.149	1.099	0.000	53.850	1.104	0.003	4.336	-0.019	0.311
2	8	40.306	0.690	-0.015	40.324	0.733	-0.013	-0.839	0.084	0.665
2	9	42.910	0.798	-0.008	43.086	0.807	-0.009	-1.965	0.130	0.497
3	1	97.272	2.834	0.031	96.899	2.853	0.033	4.689	-0.013	0.273
3	2	69.897	2.388	-0.000	68.273	2.407	0.012	1.897	0.065	0.207
3	3	76.539	1.396	-0.018	75.542	1.407	-0.011	-0.592	0.098	-0.240
3	4	79.003	1.689	-0.004	82.475	1.541	-0.027	-9.226	0.217	-0.065
3	5	91.634	1.853	-0.028	88.124	1.992	-0.001	-8.210	0.187	-0.037
3	6	66.583	1.601	-0.023	64.011	1.674	-0.003	-2.677	0.164	-0.010
3	7	44.787	1.538	0.005	44.744	1.551	0.006	-1.707	0.192	-0.183
3	8	39.638	1.884	0.058	42.566	1.747	0.033	-1.702	0.180	0.265
3	9	65.648	2.960	-0.008	55.124	3.131	0.064	1.737	0.161	0.753
3	10	84.156	3.316	0.007	84.100	3.314	0.008	1.916	0.025	0.081
4	1	49.674	1.239	0.028	50.504	1.214	0.021	-0.172	0.061	0.365
4	2	44.061	0.557	-0.031	43.462	0.540	-0.027	1.356	0.097	0.082
4	3	53.544	0.575	-0.012	53.471	0.569	-0.011	1.187	0.040	0.174
4	4	55.568	0.420	-0.024	55.328	0.414	-0.022	-1.856	0.113	-0.010
4	5	55.344	0.720	-0.017	55.282	0.720	-0.017	-0.106	0.069	-0.038
4	6	46.096	0.658	-0.012	45.903	0.665	-0.010	-0.985	0.092	0.328
4	7	43.346	0.727	-0.007	42.776	0.739	-0.003	-3.179	0.154	-0.050
4	8	55.083	1.198	-0.007	55.094	1.198	-0.007	3.772	0.032	-0.010
4	9	32.392	0.665	-0.003	32.197	0.671	-0.001	2.527	0.045	-0.085
4	10	44.327	0.483	-0.001	44.024	0.491	0.001	-4.188	0.148	-0.085
5	1	50.628	0.707	-0.010	50.383	0.710	-0.008	-3.080	0.121	0.054
5	2	36.707	0.635	-0.020	33.894	0.716	0.000	-4.728	0.274	0.159
5	3	48.074	0.660	-0.002	48.435	0.649	-0.005	-2.800	0.128	0.327
5	4	42.618	0.806	-0.005	41.538	0.828	0.003	-1.376	0.144	0.069
5	6	44.265	0.852	-0.005	44.407	0.854	-0.006	-2.520	0.145	0.172
5	7	39.097	0.647	-0.009	39.468	0.642	-0.012	-3.983	0.219	-0.073
5	9	31.223	0.776	-0.010	30.914	0.776	-0.007	0.913	0.091	0.119
5	10	43.475	0.692	-0.006	42.083	0.724	0.005	-3.142	0.160	0.469

Table 1, continued

C	R	OLS β_0	OLS β_1	OLS β_2	GLS β_0	GLS β_1	GLS β_2	GLS α_0	GLS α_1	GLS ρ
6	1	71.765	0.893	-0.018	68.733	0.890	0.004	15.207	-0.160	0.158
6	2	51.924	1.272	-0.034	51.757	1.243	-0.033	5.333	0.045	0.304
6	5	62.520	1.481	-0.040	62.883	1.495	-0.042	1.821	0.079	0.314
6	6	48.541	0.997	-0.014	47.289	1.010	-0.005	-1.677	0.145	0.430
6	7	33.228	0.675	-0.012	32.524	0.691	-0.007	-1.398	0.149	0.107
6	8	41.162	1.280	0.002	41.177	1.275	0.002	-0.055	0.084	0.240
6	9	50.497	0.912	-0.042	50.053	0.900	-0.038	2.246	0.038	0.446
6	10	48.045	0.632	-0.063	46.803	0.578	-0.050	7.765	-0.045	0.756
7	1	2.062	0.014	-0.000	1.984	0.016	0.000	0.861	-0.308	0.319
7	5	1.001	0.010	0.000	1.014	0.010	0.000	0.153	0.041	0.306
7	6	0.917	0.008	0.000	1.013	0.010	-0.001	-0.120	0.294	0.408
7	7	0.903	0.016	0.000	0.955	0.015	-0.000	-0.111	0.270	0.026
7	8	1.137	0.015	-0.000	1.251	0.016	-0.001	-0.181	0.290	0.339
7	9	0.735	0.007	-0.000	0.763	0.008	-0.000	-0.063	0.229	0.290
7	10	1.888	0.017	0.000	1.885	0.017	0.000	0.396	-0.111	0.386
8	2	23.056	0.456	-0.003	22.710	0.458	-0.001	-0.124	0.139	0.124
8	3	24.901	0.306	-0.004	24.909	0.305	-0.004	1.925	0.026	-0.132
8	4	24.731	0.478	0.006	24.501	0.483	0.008	-0.284	0.096	-0.068
8	5	30.053	0.386	-0.003	29.469	0.403	0.001	-3.413	0.182	0.131
8	6	23.865	0.213	-0.007	23.952	0.216	-0.008	-0.764	0.106	-0.009
8	7	21.393	0.184	-0.011	21.365	0.187	-0.011	-0.334	0.119	-0.163
8	8	22.294	0.154	-0.008	22.287	0.153	-0.008	7.112	-0.235	-0.069
8	9	23.083	0.278	-0.015	22.397	0.244	-0.008	9.450	-0.335	0.172
9	1	3.299	0.046	-0.000	3.297	0.046	-0.000	0.022	0.014	0.113
9	2	1.487	0.023	-0.000	1.442	0.024	0.000	-0.171	0.216	-0.005
9	3	1.996	0.026	-0.000	2.002	0.025	-0.000	0.119	-0.011	0.419
9	4	2.532	0.030	-0.001	2.577	0.027	-0.001	-0.341	0.223	0.136
9	5	2.294	0.029	-0.001	2.321	0.027	-0.001	-0.162	0.127	-0.251
9	6	1.600	0.019	-0.000	1.589	0.019	-0.000	-0.028	0.080	0.190
9	7	1.755	0.041	-0.001	1.688	0.043	-0.000	-0.030	0.100	0.299
9	8	1.672	0.027	-0.000	1.669	0.027	-0.000	0.165	-0.030	0.080
9	9	1.809	0.033	-0.001	1.772	0.033	-0.000	0.044	0.064	0.164
9	10	2.167	0.030	-0.000	2.164	0.030	-0.000	0.009	0.022	0.190

Table 2. Stochastic Trend Results Results: 1950-1989

C	R	r_2
1	1	0.020
1	2	0.044
1	3	0.166
1	4	0.005
1	5	0.000
1	6	0.075
1	7	0.017
1	8	0.000
1	9	0.057
1	10	0.011
2	1	0.000
2	8	0.270
2	9	0.171
3	1	0.146
3	2	0.000
3	3	0.016
3	4	0.000
3	5	0.017
3	6	0.017
3	7	0.000
3	8	0.468
3	9	0.306
3	10	0.005
4	1	0.177
4	2	0.058
4	3	0.019
4	4	0.031
4	5	0.025
4	6	0.034
4	7	0.007
4	8	0.000
4	9	0.000
4	10	0.000
5	1	0.020
5	2	0.274
5	3	0.177
5	4	0.000
5	6	0.000
5	7	0.011
5	9	0.015
5	10	0.073

C	R	r_2
6	1	0.174
6	2	0.037
6	5	0.059
6	6	0.021
6	7	0.026
6	8	0.000
6	9	0.177
6	10	0.317
7	1	0.124
7	5	0.087
7	6	0.083
7	7	0.000
7	8	0.100
7	9	0.082
7	10	0.151
8	2	0.000
8	3	0.000
8	4	0.025
8	5	0.000
8	6	0.030
8	7	0.038
8	8	0.018
8	9	0.064
9	1	0.000
9	2	0.000
9	3	0.000
9	4	0.240
9	5	0.065
9	6	0.024
9	7	0.100
9	8	0.097
9	9	0.067
9	10	0.054

Table 3. Monte Carlo Simulation Results

	Mean Prediction	RMSE	MAD	Efficiency
	** t=1	Ey=34.60 **		
OLS	34.49	25.58	18.59	.67
GLS	37.25	27.81	19.22	.64
ML	39.53	16.40	12.38	
	** t=20	Ey=57.71 **		
OLS	58.75	17.59	13.21	.69
GLS	57.24	17.44	13.35	.68
ML	55.65	11.13	9.07	
	** t=40	Ey=65.95 **		
OLS	64.82	35.84	26.87	.65
GLS	67.42	38.09	28.07	.62
ML	72.61	23.61	17.52	