Modeling Technical Change in Midwest Corn Yields, 1895-2005: A Time Varying-Regression Approach

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Abstract: This paper explores the use of time-varying regression models to model the effects of technical change in US Midwest Corn yields. The data extends from 1895 to 2005 encompassing the implementation of hybrid technologies and improvements in farm production practices.

Key words: time-vary regression model, modeling technical change, corn yield technical change

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1. Introduction

Corn comes into the life of every American every day. It can be as obvious as roasted corn on the cob or in the form of milk, eggs, or meat. There is, currently, strong interest in using corn to produce energy in the form of biofuels. Because of modern society's dependence on corn, it is important to gain a deeper understanding of the factors that have affected and will likely continue to affect corn yield over time.

Corn yields have increased dramatically over the past century. Illinois, for example, had an average yield of 41 bushels per acre in 1895, while in 2005 yields averaged 143 bushels per acre. The past improvements in technology include the transition from open pollination to double cross hybrids and from double cross to single cross hybrids. Other major contributions have come from the use of nitrogen fertilizers and the steady improvement in farm production practices. In fact, Griliches (1957) used the adoption of hybrid corn as an example of the pattern and effects of the diffusion of technology.

This research will utilize data beginning in 1895 to model the trend of corn yield in the top seven corn producing states: Illinois, Indiana, Iowa, Minnesota, Missouri, Nebraska and Ohio. The model will include variables for weather to enable study of the interaction between yield and weather. Past research has found that weather can influence the effectiveness of innovation and can affect the year-to-year variability of corn yields (Perrin and Heady 1975). A variety of variables representing weather have been used in the literature with mixed results. This research will use the Palmer Index, created by Wayne C. Palmer (1965), because the index incorporates temperature, precipitation, evapotranspiration, soil type and the conditions of the previous period. There will be weather variables for two critical times in the biological process of corn; one for spring planting time and the other for July when corn is in stages of silk and dough (National Agricultural Statistics Service).

There are four objectives of this research:

1. To explore the use of a logistic time-varying regression approach to modeling corn yield data,
2. To examine the influence of weather on yields and, as well, to attempt to determine if weather effects in corn yields have shifted over time,
3. To examine the relative variance of corn yields over time to determine if yield variance has changed, and
4. To compare a time-varying regression model to a model using a linear segmented trend.

First, this paper explores the use of a logistic time-varying regression approach to modeling corn yield data. The time-varying regression is a particular type of smooth transition regression. Bacon and Watts (1971) were the first to suggest a smooth transition model to illustrate how experimental data which appear to behave according to different distinct linear relationships transition from one extreme linear parameterization to another as a function of the continuous transition variable. The time-varying regression approach allows for nonlinear trends and, as well, requires that the trend, i.e., the proxy for technical change, be a bounded, monotonically increasing function (Teräsvirta 1996). This approach seems particularly suitable to modeling corn yield.

Second, the model will include variables representing weather. Because weather influences corn production, it is necessary to control for these effects in the analysis. Following Perrin and Heady (1975), this research will use the Palmer Index unlike most other research that has used elementary variables of temperature and precipitation. The effects of the Palmer Index on corn yields will also be allowed to vary over time in an attempt to determine if there has been a shift in the sensitivity of yields to weather.

Third, the relative variance of corn yields will be examined to see if they have become more or less variable over time. Numerous studies (Perrin and Heady 1975; Offutt, Garcia et al. 1987; Kim and Chavas 2003) have attempted to determine if there has been a change in yield variability, albeit with mixed results. The current study will use a much longer timeline than nearly all previous studies on corn yield behavior, thereby allowing comparisons of the variance of the yield-weather relationship to be made from a period of minimal technology to today's current level of sophistication.

Fourth, in this research a comparison will be made between a logistic time-varying regression model and a model using segmented trends. It is common practice for a segmented trend model beginning in 1940 to be used to model corn yields. A comparison will be made based on goodness-of-fit criterion and the possibility of using a combination of the two models will be explored.

2. Methodology

To begin, consider a simple linear regression model

$$y_i = \beta_1 + \sum_{j=2}^{k} \beta_j x_{ij} + \varepsilon_i \tag{1}$$

where β_1 is the intercept and the β_js are the coefficients measuring the effect of the explanatory variables on yield. As well, the x_{ij}s are explanatory variables, in this case including weather variables, and ε_i is an independently, identically distributed additive disturbance. An assumption of the classic linear regression model is that the "unknown coefficients of this linear function form the vector β and are assumed to be constants" (Kennedy 2003). The assumption of linearity must always be considered because linear models have been effective at approximating many socio-economic relationships. Even so, there are situations for which the underlying economic relationship is not linear (Teräsvirta 1996). Kennedy (2003) states that a violation of the linearity assumption would be a case of changing parameters. In a time series problem, it is very likely that the parameters will change over time. It is therefore necessary to construct a model that reflects this possibility.

In the simplest case a linear trend term could be added to the model

$$y_i = \beta_1 + \theta_1 t + \sum_{j=2}^{k} \beta_j x_{ij} + \varepsilon_i \tag{2}$$

where t is a trend. This simple specification allows the intercept term β_1 to change systematically over time. That is, the "moving" intercept in the model is now $\beta_1 + \theta t$. This example represents a simple case of only allowing one parameter (i.e., the intercept term) to change in a linear fashion. But what if parameter change is monotonic and bounded? Following Teräsvirta (1996), a function $G(t^*;\gamma, c)$ that acts on the parameter θ is added to create a time varying regression model. That is,

$$y_i = \beta_1 + \theta_1 G(t^*;\gamma, c) + \sum_{j=2}^{k} \beta_j x_{ij} + \varepsilon_i \tag{3}$$

where $G(.)$ denotes the so-called transition function, a function that is, moreover, bounded between zero and unity. In this case $G(.)$ is a function of t^*, where $t^* = 1/T$. That is, t^* is a transition variable for the constant change of the intercept parameter over time. The slope parameter, γ, indicates how rapidly the transition function moves from zero to one. The location parameter, c, determines at what point in time the transition from zero to unity will be 50-percent complete. The above is referred to as a time varying regression model, or TV-R, because it uses time as a transition variable instead of lagged yields or weather variables or other variables that might represent technological change.

If all of the parameters in the previous model are changing over time due, for example, to technical change, following Teräsvirta (1996) this change could be modeled simply as

$$y_i = \left[\beta_1 + \sum_{j=2}^{k} \beta_j x_{ij} \right] \left(1 - G\left(t^*;\gamma,c\right)\right) + \left[\theta_1 + \sum_{j=2}^{k} \theta_j x_{ij} \right] G\left(t^*;\gamma,c\right) + \varepsilon_i \,. \quad (4)$$

In other words, all parameters would change over time and the transition function, G, weights the parameters so that the switch from one regime to the next is smooth.

Teräsvirta and Anderson (1992) suggest a logistic function and when it is used with (1) is known as a logistic TV-R model, or LTV-R.

$$G(t^*;\gamma,c) = (1 + \exp\{-\gamma(t^* - c)\})^{-1}, \qquad \gamma > 0 \qquad (5)$$

LTV-R models allow the parameters to change, potentially, monotonically with t^*. The LTV-R function is S-shaped and because it is not linear, the slope coefficient, γ, is not constant and as the LTV-R function moves through time it smoothly transitions regimes showing periods of small adjustment with little slope, small γ coefficients, and other periods of dramatic adjustment with large γ coefficients. Applied to the corn yield models, an LTV-R model describes a situation where a transition from one technology regime to the next will be smooth.

Tests for Model Selection

The model selection criterion used is the Akaike information criterion (AIC). According to Greene (2003), the AIC is preferred to the adjusted R^2 because there is some question about whether the adjusted R^2 has a penalty large enough "to ensure that the criterion will necessarily lead the analyst to the correct model as sample size increases". The AIC will improve as "R^2

increases, but, degrade as model size increases" (Greene 2003). The value of the AIC declines as the model improves. The formula for the AIC is $AIC(K) = S_Y^2 (1 - R^2) e^{2K/n}$.

The Likelihood Dominance Criterion was used in comparison and selection. Pollak and Wales (1991) defined the mechanically nested model to be used to compare and rank two competing hypotheses. The process of comparison is done in three steps. First, to choose the first hypothesis over the second hypothesis:

$$L_2 - L_1 < [C(n_2 + 1) - C(n_1 + 1)]/2$$

where L is a log-likelihood function value, *C(.)* is a chi-squared critical value and n_i is number of independent variables in the *ith* model.

Second, there is indecision between the two hypotheses if:

$$[C(n_2 - n_1 + 1) - C(1) \geq L_2 - L_1 \geq [C(n_2 + 1) - C(n_1 + 1)]/2$$

Finally, if the second hypothesis dominates the first hypothesis then:

$$L_2 - L_1 > [C(n_2 - n_1 + 1) - C(1)]/2$$

Maximum Likelihood Estimation

Maximum Likelihood Estimation (MLE) methods are used to estimate the parameters in the LTVR model proposed. MLE is an appropriate choice because, in many cases, adopting the maximum likelihood criterion automatically generates estimates that conform to other estimating criteria, such as: consistency, asymptotic normality, asymptotic efficiency, and invariance (Greene 2003). MLE also brings the added advantage that heteroskedasticity in the variance may be readily accounted for, assuming that the distribution of the errors is known (Wooldridge 2003).

Beginning with a simple equation showing y_i, the dependent variable, it is assumed that the (possibly nonlinear) model giving the predicted values for y may be written as $h(x_i|\beta)$. By appending an additive error term, and under the assumption of normality, the model is now

$$y_i = h(x_i|\beta) + \varepsilon_i,$$

$$\varepsilon_i \sim N(0, \sigma^2), \quad i = 1, \ldots, n.$$

Let $f(\varepsilon_i|\beta)$ denote the probability density function (pdf) associated with the disturbance term, ε_i, conditional on parameters β. Assuming that $f(\varepsilon_i|\beta)$ follows a normal distribution, the model becomes

$$f(\varepsilon_i|\beta) = (2\pi\sigma^2)^{-1/2} \exp\left\{-\tfrac{1}{2}\frac{\varepsilon_i^2}{\sigma^2}\right\} \tag{1}$$

From an econometric viewpoint, the typical goal is to maximize the likelihood function with respect to the unknown parameters β. Given the assumption that the disturbance terms are independently and identically distributed, the likelihood function for a random sample of size n, which in this case may be written as:

$$L = \prod_{i=1}^{n} f(\varepsilon_i|\beta) = (2\pi\sigma^2)^{-n/2} \exp\left\{-\tfrac{1}{2}\sum_{i=1}^{n}\frac{\varepsilon_i^2}{\sigma^2}\right\} \tag{2}$$

For various reasons it is often more convenient to work with the log likelihood function, which may be expressed in this case as

$$\ln L = \sum_{i=1}^{n} \ln f(\varepsilon_i|\beta) = -\frac{n}{2}\ln(2\pi\sigma^2) - \tfrac{1}{2}\sum_{i=1}^{n}\frac{\varepsilon_i^2}{\sigma^2}$$

Of course, in the present case the maximum likelihood problem is equivalent to estimating the parameters in $h(x_i|\beta)$ by using least squares.

The picture changes, however, if the included ε_i's are heteroskedastic, that is, if it is concluded that $\varepsilon_i \sim N\left(0, \sigma_i^2\right), \quad i = 1, \ldots, n$. For example, it might be specified that $\sigma_i^2 = g\left(x_i, \theta\right)$, where θ is a set of parameters that dictate how σ_i^2 changes with x_i. In this case, the log likelihood function in (2) becomes

$$\ln L = \sum_{i=1}^{n} \ln f\left(\varepsilon_i \middle| \beta, \theta\right) = -\frac{n}{2}\ln\left(2\pi\right) - \tfrac{1}{2}\sum_{i=1}^{n} \ln \sigma_i^2 - \tfrac{1}{2}\sum_{i=1}^{n} \frac{\varepsilon_i^2}{\sigma_i^2} \qquad (3)$$

Assuming that functional forms for $h\left(x_i \middle| \beta\right)$ and $g\left(x_i, \theta\right)$ can be specified, it is then possible to use nonlinear estimation methods in conjunction with (3) to obtain parameter estimates for the mean and variance of corn yields. This approach will be pursued in this study.

3. Logistic Time Varying Regression Model Results

The equation for the logistic time-varying regression model is

$$y_i = \left(\alpha_1 + \alpha_2 JPI_i + \alpha_3 AMPI_i\right)\left(1 - G\left(t^*; \gamma, c\right)\right) + \left(\beta_1 + \beta_2 JPI_i + \beta_3 AMPI_i\right) G\left(t^*; \gamma, c\right) + \varepsilon_i$$

$$\varepsilon_i \sim N\left(0, \sigma_i^2\right)$$

where the α parameters are the coefficients when the transition function, *G*, is zero, *JPI* is the July Palmer Index value, *AMPI* is the variable for the average of the Palmer Index values for April and May, *G* is the transition function, and ε is an additive error term.

The model for *G*, the transition function, is

$$G\left(t^*; \gamma, c\right) = \left[1 + \exp\left(-\gamma\left(t^* - c\right) / \hat{\sigma}_{t^*}\right)\right]^{-1}, \quad \gamma > 0,$$

where G is a monotonically increasing function of t^*, t^* is the transition variable for the constant change of the parameters over time, γ is the slope parameter indicating how rapid the transition from zero to one is as a function of t^*, and c is the location parameter determining where the transition occurs as a function of t^*.

The model for standard deviation is

$$\sigma_i = \eta_1 + \eta_2 JPI_i + \eta_3 AMPI_i + \eta_4 t^*$$

The model for standard deviation is squared so that the variance changes over time with the variables for weather and the transition variable, t^*.

Plots of the time-varying logistic function for each of the estimated LTVR models were created (Figure 1). The figures exhibit several interesting points. First, the steepness of the curve shows the rapidity of yield increases over time. Second, the functions reveal the approximate point in time when the trend yield adjustments obtain the 50% level. Third, they display how much of the potential adjustment amount was reached in 2005. The logistic time-varying regression function for Illinois shows that in 2005 yields have reached 90% of full potential. The logistic time-varying regression function for Indiana shows that by 2005, corn yields had attained 97% of the total potential. For Iowa, the logistic time-varying regression function shows that by 2005, yields had achieved 89% of the total adjustment amount. The logistic time-varying regression function for Minnesota shows that by 2005, yields had only achieved 69% of the total adjustment amount. The difference in the trend in Minnesota can, in part, be explained by the fact that, according to data from NASS, harvested acres has increased more in that state over the period of study than the other states. For Missouri, the logistic time-varying regression function shows that by 2005, yields had achieved 94% of the total adjustment amount. The logistic time-varying regression function for Nebraska shows that by 2005, yields had achieved 97% of the total adjustment amount. For Ohio, the logistic time-varying regression function shows that by 2005, yields had achieved 92% of the total adjustment amount.

The Logistic Time-Varying Regression Weather Parameters

In the regression results just reviewed it was found that the β coefficient values are greater, in absolute terms, than the α coefficient values. This means that the influence of weather in the latter part of the sample was typically stronger than in the beginning of the sample. The imputed values for these coefficients at each point in time were therefore determined. The imputed value for the July Palmer Index at any point in time is simply

$$f(JPI) = (\alpha_2(1-t^*)) + (\beta_2(t^*)),$$

where α_2 is the coefficient of the July Palmer Index for the early portion of the sample, t^* is the time trend and β_2 is the coefficient of the July Palmer Index at the latter part of the time period. Likewise, the imputed value for the April-May Palmer Index at any point in time is

$$f(AMPI) = (\alpha_3(1-t^*)) + (\beta_3(t^*)).$$

These imputed parameter values may then be plotted against time.

This section contains graphs in Figure 2 for each state showing the trend in these parameters over time. Each figure has the parameter values for the July Palmer Index and for the April-May Palmer Index. The July line is the top of the graph because those values are typically positive and the April line is on bottom, because those values are typically negative. All of the states show an increase in yield sensitivity to weather. This is in contrast to that of Perrin and Heady (1975) where they stated that the direct effect of moisture stress has not changed.   Perrin and Heady did find evidence that an increased impact through indirect effects may have begun to occur in Illinois due to increased use of nitrogen. Illinois, Indiana, Iowa and Ohio begin with fairly small parameters values that increase noticeably over time. The figure for Minnesota reflects the fact that the weather parameters are not significant in the early portion of the model. The graph for Missouri shows that the weather parameters are greater in the beginning as compared to the other states and do not change as dramatically. The graph for Nebraska shows the weather parameter for April-May increased more dramatically than the parameter for July. A possible explanation is that irrigation is commonly used in this state, which would reduce the influence of weather in July.

Coefficient of Variation for Logistic Time-Varying Regression Model

An objective of this research was to find if the relative variability of corn yields had decreased over time. The coefficient of variation represents the relative variance. Relative variance is more important to study in this case than the absolute variance because of the dramatic increase in total yields over the 111 year period. To find the moving intercept for the coefficient of variation divide the moving intercept of the standard deviation by the moving intercept of the mean. The model for the moving intercept of the coefficient of variation is

$$f\left(CV\right)=\frac{f\left(stdev\right)}{f\left(\mu\right)}=\frac{\left[\eta_1+\eta_4 t^*\right]}{\left[\left[\alpha_1\left(1-G\left(t^*;\gamma,c\right)\right)\right]+\left[\beta_1\left(G\left(t^*;\gamma,c\right)\right)\right]\right]}$$

In every state, the moving intercept for the coefficient of variation peaks from 1935 to 1940 and appears to have stabilized over the past 20 years. These results are in concurrence with the findings of Offutt, et al. (1987). This section contains graphs of the coefficient of variation for each state in Figure 3. Each figure displays the coefficient of variation over time and the moving intercept of the coefficient of variation. The more dispersed the coefficient of variation is around the moving intercept indicates greater relative variance.

4. Comparison of the LTVR Model to a Model with Segmented Trend

Many economists have argued that a segmented trend beginning in 1940 could, and perhaps should, be used to model corn yields over time. This conjecture was examined by creating a segmented trend for all of the states and then comparing those regression results with that of the LTVR model. The segmented trend model was specified by interacting a dummy variable that contains “0” prior to 1940 and “1” thereafter with the other parameters in the model. That is, the model for the segmented trend is

$$f(segmentedtrend) = \left[(\alpha_1 + \alpha_2 JPI_t + \alpha_3 AMPI_t + \alpha_4(t^*)) \times (1 - DUM40)\right]$$

$$+ \left[(\beta_1 + \beta_2 JPI_t + \beta_3 AMPI_t + \beta_4(t^*)) \times DUM40\right] ,$$

where α_1 is the intercept for the beginning of the time period, α_4 is the coefficient for a trend term, β_1 is the intercept for the latter portion of the period and β_4 is the trend coefficient.

There are also economists that question the existence of a trend in corn yields prior to 1940, and therefore, inclusion of a trend term for the early period is examined. L_{ur} is the log likelihood value of the unrestricted model including a trend term for the early period. L_r is the log likelihood value for the model restricted to exclude the early trend term, $\alpha_4(t^*)$. The likelihood ratio and corresponding p-values are calculated. Table 1 displays the results where Illinois, Iowa, Nebraska and Ohio show no evidence, at the 5% level, that there is trend in corn yields prior to 1940. There is trend in corn yields prior to 1940 in Indiana, Minnesota and Missouri.

In Figure 4, the segmented trend is plotted along with the moving intercept of the LTVR model and the actual yield observations. For most of the states, except Minnesota, the moving intercept is below the segmented trend by 2005.

Comparing the LTVR Model to the Model with Segmented Trend

The regression results of the model with segmented trend are compared to those of the LTVR model. The criterion used for comparison is the likelihood function value, the Akaike Information Criterion, and the Likelihood Dominance Criterion. The likelihood function value should only be used in states with the same numbers of parameters because, by definition, a model with a greater number of parameters should have a higher likelihood value. Recall that the difference in the numbers of parameters comes from the inclusion or exclusion of the trend term in the early period. The Akaike Information Criterion (AIC) can be used for comparison in every case because it is adjusted for the number of parameters and will, by design, punish models that are over-parameterization. The final value for comparing the Likelihood Dominance Criterion and the steps for this calculation are outlined in the methodology chapter. It is appropriate to use the Likelihood Dominance Criterion when there are different numbers of parameters. When the models have the same number of parameters, the criterion dictates that whichever has the highest likelihood value is the better model. In Table 2, first compare the value of the difference in the likelihood function values to the value in the following column, labeled $[C(n_2+1)-C(n_1+1)]/2$. If the difference is less than $[C(n_2+1)-C(n_1+1)]/2$, then choose the segmented trend model over the LTVR model. Next, compare the value of the difference in likelihood values to the last column, labeled $[C(n_2-n_1+1)-C(1)]/2$. If the value in the difference between the likelihood values is greater than the value from $[C(n_2-n_1+1)-C(1)]/2$ then choose the LTVR model over the segmented model.

Table 2 shows the comparison criterion for each state. For Illinois, the likelihood function values cannot be compared because of the difference in the number of parameters, the AIC indicates that the segmented model is preferred, but the results of the Likelihood Dominance Criterion are mixed. Therefore, Illinois has a slight preference for a model with segmented trend. For Indiana, the LTVR model has a greater likelihood function value, better AIC value and the likelihood dominance criterion defers to the likelihood values. Based on this criterion, the LTVR model is better suited to the data for Indiana. For Iowa, the likelihood values cannot be compared, the segmented model has a higher AIC value and the likelihood dominance criterion indicate that the segmented trend is better for this state. For Minnesota, the LTVR model is more suitable based on the likelihood values and the AICs. In Missouri, the likelihood values and AICs give evidence that the segmented trend is better. All criterions for comparison indicate that the LTVR model does a better job explaining the yield data in Nebraska. Finally, the criterions for Ohio imply that the model with segmented trend is more appropriate.

Encompassing Regressions

Due to the close comparisons in some of the states, the opportunity to use a combination of these two models was explored. This equation shows an encompassing regression.

$$y_t = \alpha_0 + \alpha_1\left(\hat{y}_{LTVR}\right)_t + \alpha_2\left(\hat{y}_{SEGMENTED}\right)_t + \varepsilon$$

where y is the actual yield data, $\hat{y}_{LTVR}$ is the predicted values from the LTVR model, $\hat{y}_{SEGMENTED}$ is the predicted values from the segmented model, and ε is an additive error term. By regressing the actual yield on the predicted values from both of the models in combination, the significance of the two models in explaining the change in yield is found. In Table 3, the results of the regressions for each state are shown. The LTVR model is significant, at the 5% level, for all of the states, except Iowa. The segmented model is significant in Indiana, Iowa, Missouri and Nebraska. These results suggest that some weighted combination of the LTVR and segmented models should be used.

5. Summary and Conclusions

In this paper, we explored the use of logistic time-varying regression approach for modeling corn yield behavior. We found that the smooth transition model did indeed capture the transition from one regime of corn technology to the next quite nicely. Using the LTVR approach, the weather parameters were allowed to change over time and the subsequent plots showed an increase in yield sensitivity to weather. A potential reason for this could be that with the improvement in technology and farm management practices, a greater portion of the variability is caused by weather today than in the past. The relative variance decreased for all of the states but, the dispersion of the coefficient of variation around the moving intercept trend has increased indicating that weather and other factors not included in the model are causing the variability.

The comparison of the LTVR model to that of a segmented trend had mixed results. Various criterion were used to determine which was more suitable and because the diagnostics were so similar, an encompassing regression was computed. The encompassing regression found that the LTVR model was significant in explaining the variability of corn yields in every state, except Iowa. In the context of using these models to forecast, exclusively using a model with segmented trend would “over-predict” the potential future yields. This research suggests using a weighted combination of the two models would be ideal if the goal is to predict potential yields.

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List of Tables

Table 1. Likelihood Ratios Comparing Models With and Without a Trend Term Prior to 1940.

	Illinois	Indiana	Iowa	Minnesota	Missouri	Nebraska	Ohio
L_{ur}	192.954	208.192	177.858	187.733	171.141	170.748	213.385
L_r	192.271	205.787	176.895	183.948	168.671	170.597	212.231
p-value	0.242	0.028	0.165	0.006	0.026	0.583	0.129

Table 2. The criterion used to compare the LTVR model to the Segmented Trend model.

		Likelihood Function Value	Number Parameters	Akaike Information	Likelihood Dominance Criterion L_{seg}-L_{LTVR}	$[C(n_2+1)-C(n_1+1)]/2$	$[C(n_2-n_1+1)-C(1)]/2$
Illinois	LTVR	193.098	12	-169.098	0.827	0.668	1.075
	Segmented	192.271	11	-170.271			
Indiana	LTVR	210.444	12	-186.444	2.252	0.000	0.000
	Segmented	208.192	12	-184.192			
Iowa	LTVR	176.135	12	-152.135	-0.761	0.668	1.075
	Segmented	176.895	11	-154.895			
Minnesota	LTVR	189.845	12	-165.845	2.111	0.000	0.000
	Segmented	187.733	12	-163.733			
Missouri	LTVR	169.789	12	-145.789	-1.352	0.000	0.000
	Segmented	171.141	12	-147.141			
Nebraska	LTVR	180.613	12	-156.613	10.015	0.668	8.592
	Segmented	170.597	11	-148.597			
Ohio	LTVR	207.895	12	-183.895	-2.555	0.668	1.075
	Segmented	210.450	11	-188.450			

Table 3. The Results of the Encompassing Regressions.

	Coefficient	Std. Error	T-Statistic	P-Value
Illinois				
constant	-0.019	0.028	0.701	0.485
Predicted LTVR	0.599	0.262	2.287	0.024
Predicted Segmented	0.409	0.255	1.600	0.113
R^2	0.942			
Indiana				
constant	-0.004	0.025	0.167	0.868
Predicted LTVR	0.601	0.170	3.541	0.001
Predicted Segmented	0.401	0.171	2.346	0.021
R^2	0.951			
Iowa				
constant	-0.001	0.032	0.024	0.981
Predicted LTVR	0.291	0.323	0.902	0.369
Predicted Segmented	0.712	0.321	2.218	0.029
R^2	0.923			
Minnesota				
constant	-0.015	0.031	0.498	0.619
Predicted LTVR	0.686	0.216	3.180	0.002
Predicted Segmented	0.328	0.223	1.471	0.144
R^2	0.932			
Missouri				
constant	-0.003	0.032	0.092	0.927
Predicted LTVR	0.557	0.198	2.820	0.006
Predicted Segmented	0.442	0.194	2.275	0.025
R^2	0.928			
Nebraska				
constant	-0.006	0.021	0.283	0.778
Predicted LTVR	0.716	0.147	4.883	0.000
Predicted Segmented	0.288	0.147	1.960	0.053
R^2	0.969			
Ohio				
constant	-0.011	0.026	0.435	0.664
Predicted LTVR	0.654	0.232	2.819	0.006
Predicted Segmented	0.355	0.233	1.527	0.130
R^2	0.947			

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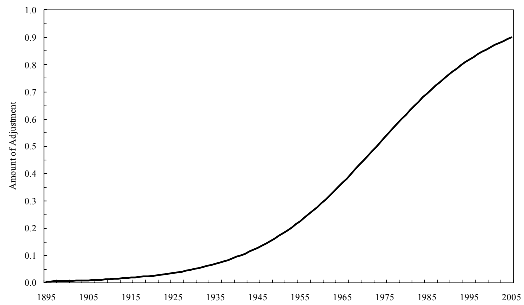

Figure a. Illinois LTVR.

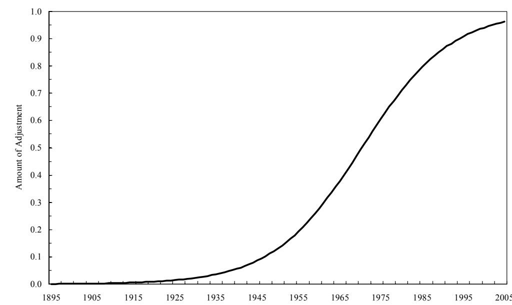

Figure b. Indiana LTVR.

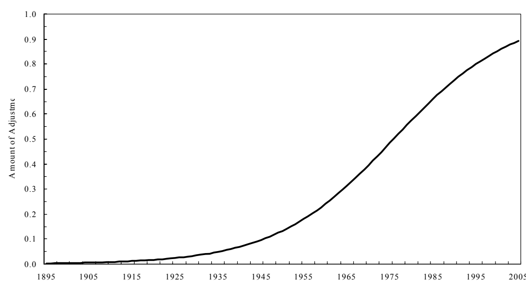

Figure c. Iowa LTVR.

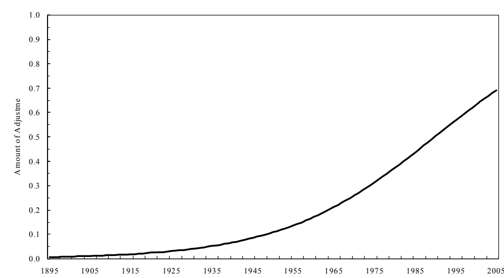

Figure d. Minnesota LTVR.

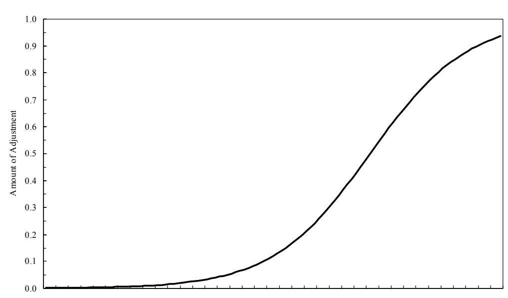

Figure e. Missouri LTVR.

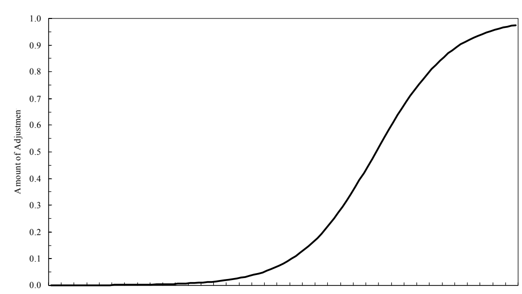

Figure f. Nebraska LTVR.

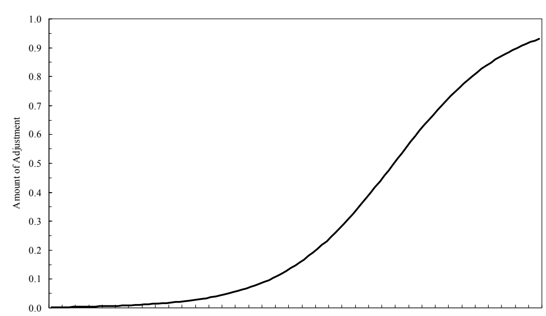

Figure g. Ohio LTVR.

Figure 1. The logistic time varying function of the conditional mean.

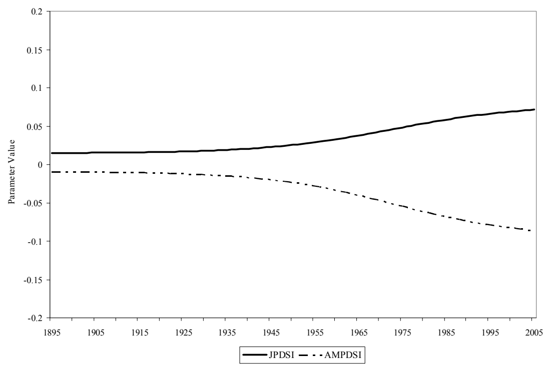

Figure a. Illinois weather parameters over time.

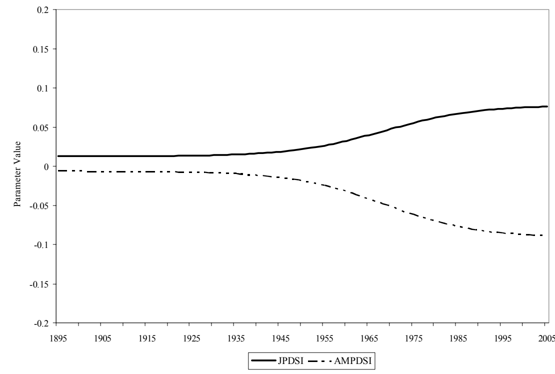

Figure b. Indiana weather parameters over time.

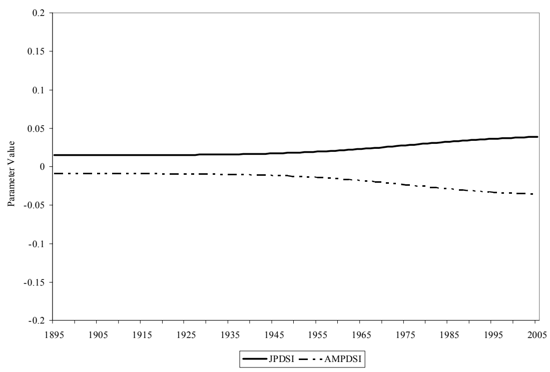

Figure c. Iowa weather parameters over time.

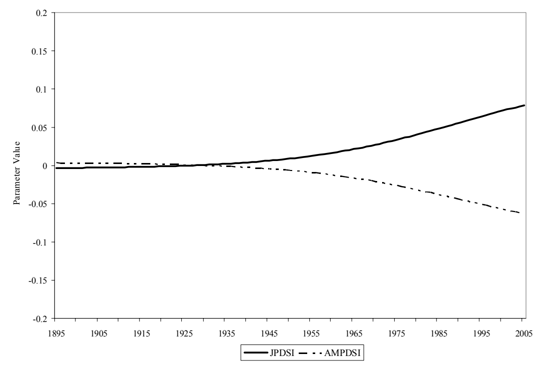

Figure d. Minnesota weather parameters over time.

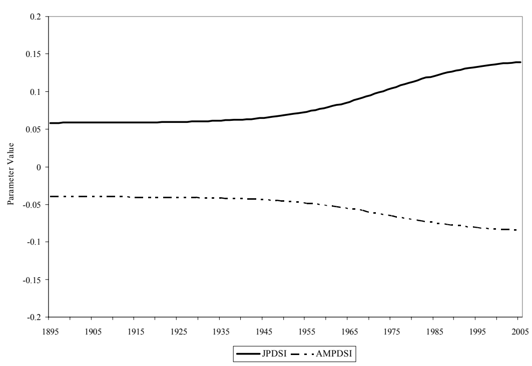

Figure e. Missouri weather parameters over time.

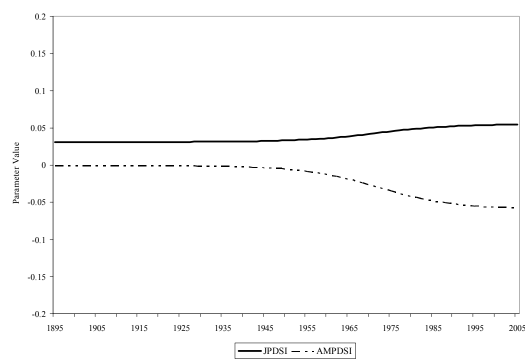

Figure f. Nebraska weather parameters over time.

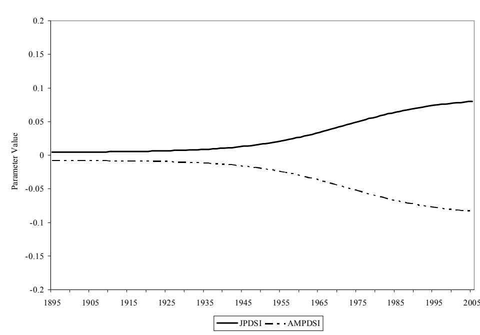

Figure g. Ohio weather parameters over time.

Figure 2. The figures for all of the states showing how the weather parameters change over time.

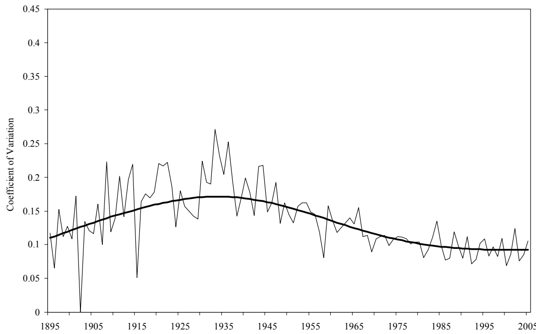

Figure a. Illinois coefficient of variation

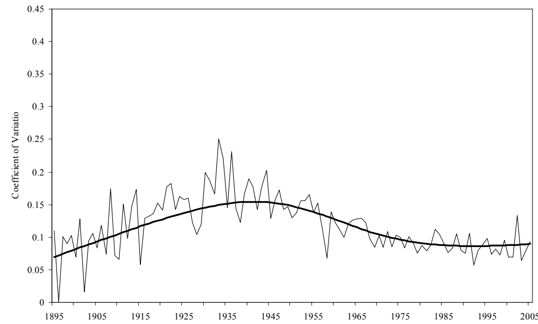

Figure b. Indiana coefficient of variation

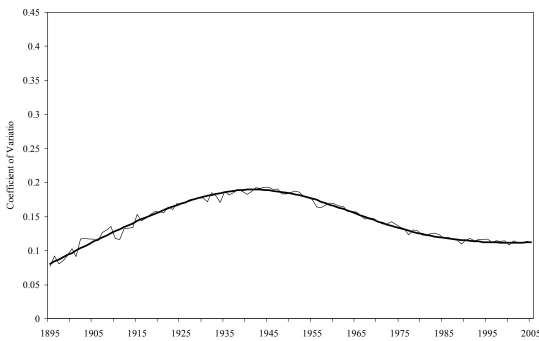

Figure c. Iowa coefficient of variation

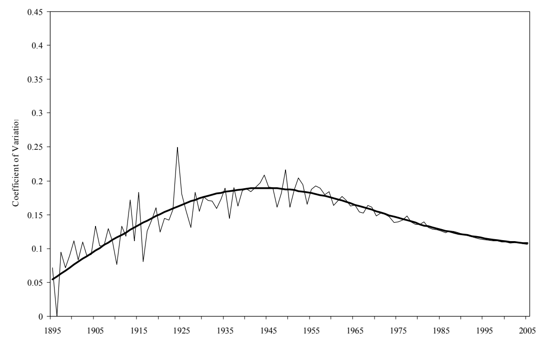

Figure d. Minnesota coefficient of variation

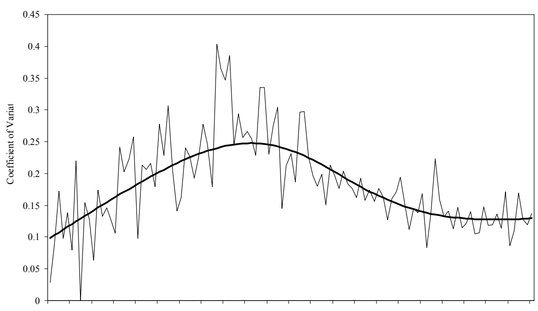

Figure e. Missouri coefficient of variation

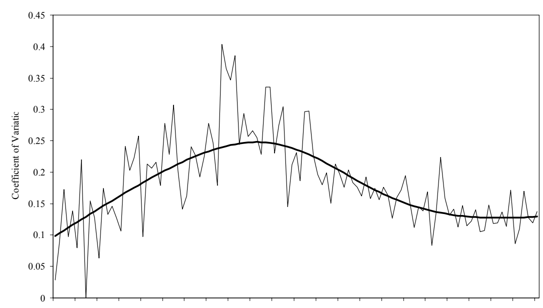

Figure f. Nebraska coefficient of variation

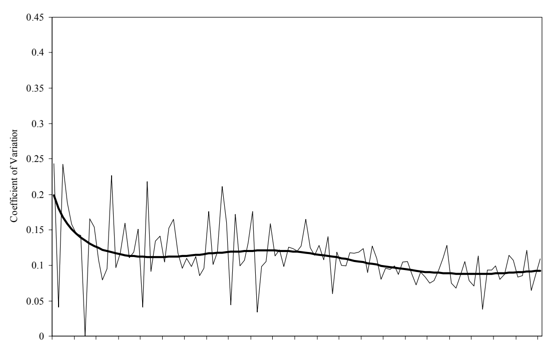

Figure g. Ohio coefficient of variation

Figure 3. The graphs of the coefficient of variation for the seven states.

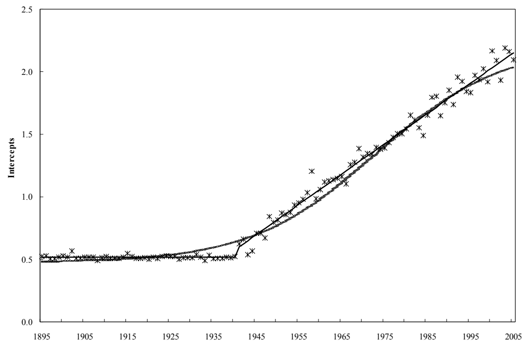

Figure a. Illinois.

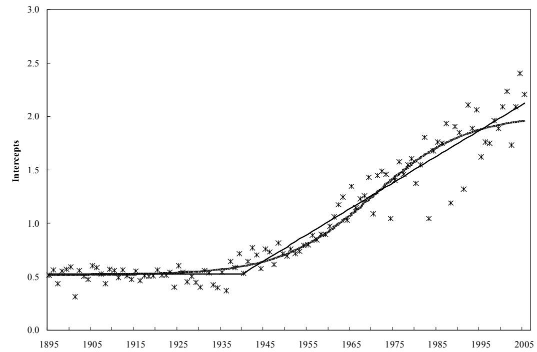

Figure b Indiana.

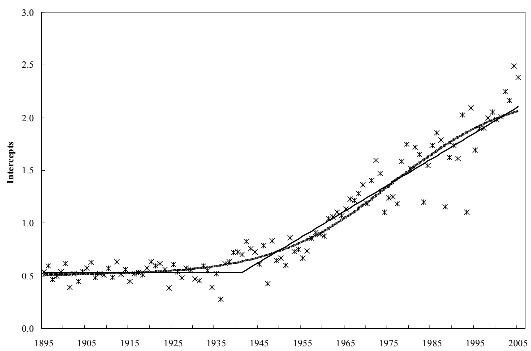

Figure c. Iowa.

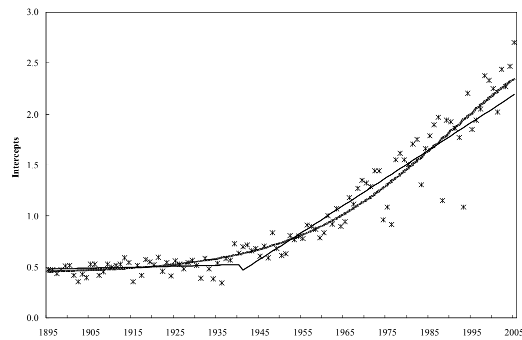

Figure d. Minnesota.

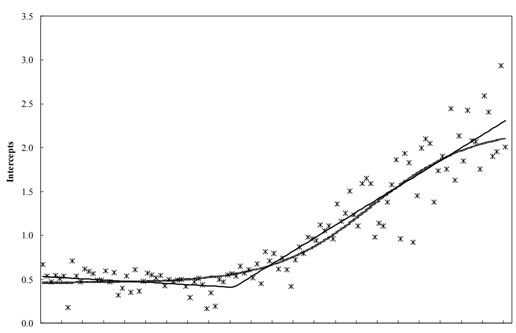

Figure f. Missouri.

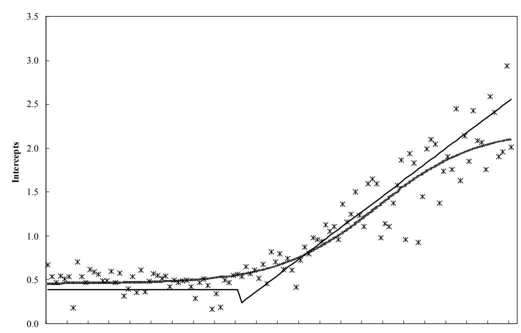

Figure g. Nebraska.

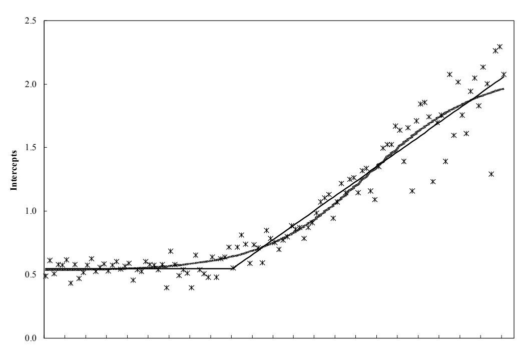

Figure h. Ohio.

Figure 4. The plot of the segmented trend, moving intercept, and normalized yields.