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### A Robust Study of Regression Methods for Crop Yield Data

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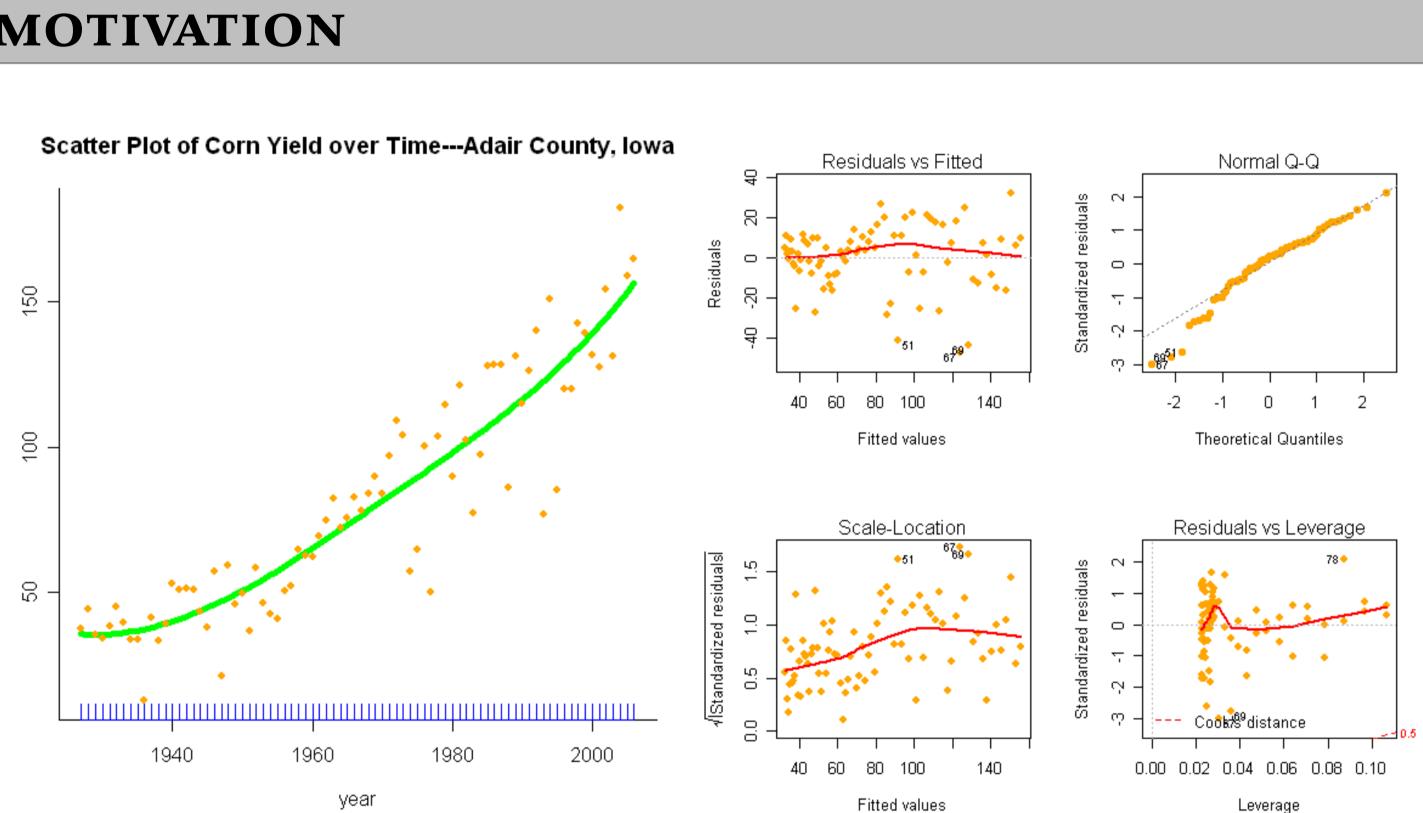
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### **OBJECTIVE**

- Precisely estimating crop yield risk is crucial for the proper design and rating of crop insurance contracts
- Advances in biotechnology and changes in environmental conditions may significantly affect the distributions of crop yields
- These changes can complicate efforts to accurately model yield distributions using time series data
- The objective of this study is to evaluate the robust regression methods when detrending the crop yield data. We analyze the properties of robust estimators for outliers contaminated data in both symmetric and skewed distribution case.

### **MOTIVATION**



The figure above gives the plot of the county-level corn yield. It shows:

- Upward time trend—we need to estimate/remove the trend when model yield distribution
- Outliers: Outliers can shift trend estimation arbitrarily far from the real
- Skewed: Left-skewed from Q-Q plots—an indication for non-normality
- Heteroscedastic: Non-constant coefficient variance—errors are proportional to mean

### **A SIMPLE DETRENDING REGRESSION**

Consider the following trend model:

$$y_t = \beta_0 + \beta_1 t + \epsilon_t$$

- $y_t$  is the observed crop yield in year t, (t = 1, ..., T),
- $\bullet \epsilon_t$  represent residuals that are assumed to be independently distributed with mean zero:  $E(\epsilon_t) = 0$  and  $var(\epsilon_t) = \sigma_t^2$

## AAEA 2011, Pittsburgh, Pennsylvania

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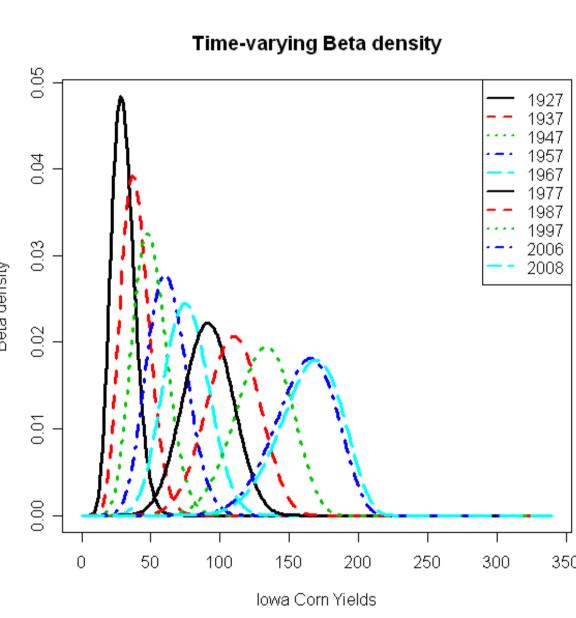
\* SAS Institute, Inc, Cary, NC \*\* North Carolina State University, Raleigh, NC Presented at AAEA 2011, Pittsburgh, Pennsylvania, July 24-26, 2011

### THE ROBUST REGRESSION METHODS

We consider the following robust regression techniques for the detrending of crop yield data:

- ► OLS
- ► M estimation introduced by Huber (1973)
- MM estimation introduced by Yohai (1987)
- Time-varying Beta method by Zhu, Goodwin and Ghosh (2011)

### TIME-VARYING BETA DENSITY PLOTS BASED ON MLE ESTIMATES



- Above figure shows time-varying Beta density plot:  $y_t \sim Beta(\alpha_t, \beta_t, \theta_t, \delta_t)$
- The density plots show that various moments of the distributions evolve over time as the technology progresses

### **MONTE CARLO SIMULATIONS**

- The Monte Carlo simulation is used to study the performance of the candidate robust regression method.
- The simulation parameter is chosen to be consistent with the robust study in the previous literatures (Swinton and King (1991))
- Fix  $\beta_0$ ,  $\beta_1$  for some positive numbers
- Yield series are generated assuming a known trend of  $\beta_1$  and a random error with variance  $\sigma_t^2$

### SIMULATION UNDER SYMMETRIC AND SKEWED DISTRIBUTIONS

- Symmetric Normal Distribution:  $\epsilon_t \sim N(\mu = 0, \sigma = \sigma_t)$
- Skewed Beta Distribution:  $\epsilon_t \sim 6\sigma_t(Beta(10, 6) \frac{5}{8})$
- Set  $\sigma_t = 25t^{\alpha}$ , where  $\alpha \in [0, 1)$ .
- This variance form introduces a general outlier generating form when  $\alpha$ equals to any nonzero number. The largest variance will occur at the end of the series
- Both the distributions are designed properly so that  $\sigma_t = 125$  when t = T
- ► Set  $T \in \{10, 15, 20, 25\}$  and  $\alpha \in \{0, 0.1, 0.2, \frac{\log 5}{\log T}\}$
- Different value of sample size T and  $\alpha$  stands for different outlier contamination scenarios

### **EMPIRICAL RESULTS**

- of  $\alpha$  and *T*.

distribution and sample size



- regression methods
- the simulated series
- different estimation methods



1000 datasets are generated under each distribution with different value

The identical simulated yield series are fitted using OLS, M estimator, MM estimator, time-varying Beta models

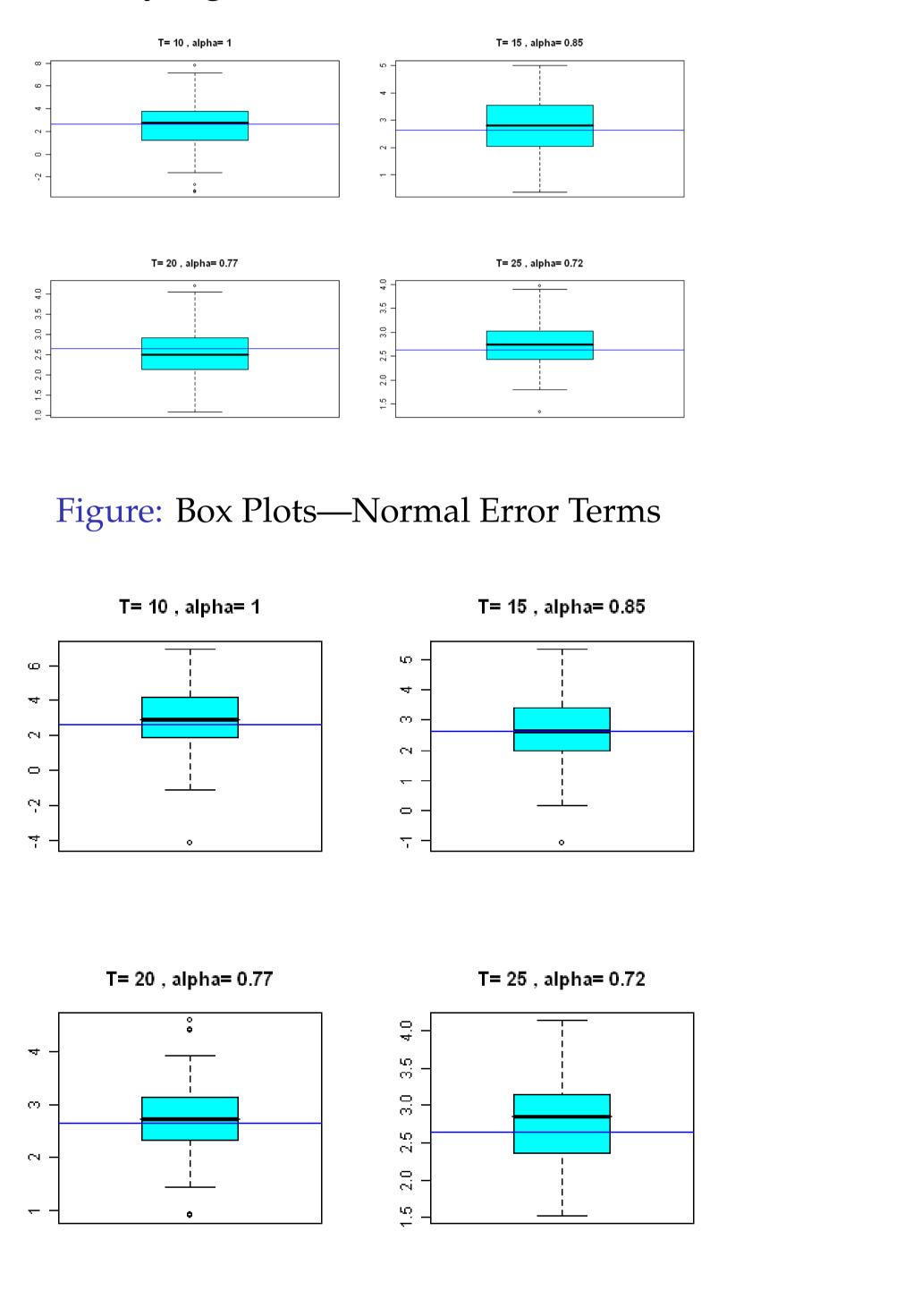


Figure: Box Plots—Beta Error Terms

Above figure shows an example of box plots for OLS estimates for each

# **MODEL PERFORMANCE AND ECONOMICS**

Boxplots of OLS, M estimates, MM estimates and time-varying Beta estimates allow us to compare the in-sample robustness of these

The performance of the candidate robust estimators is assessed in terms of trend estimation, out-of-sample prediction of future yield levels using

Implication of crop insurance rate estimation is analyzed based on