On Technological Change in Crop Yields

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Technological Change in Agriculture

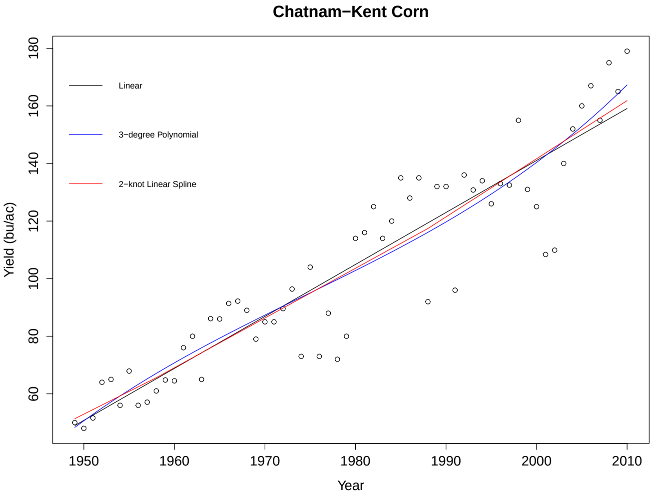
Invention, diffusion and adoption of new technology

- Crops and crop varieties
- Tools (irrigation, fertilizer)
- Methods (tillage, rotation)

Impacts of technological change

- Food sustainability
- Economic growth and development
- World hunger
- Energy (i.e. biofuels)
- Mitigation of potential climate change effects

Measuring Technological Change in Agriculture



Measuring Technological Change in Agriculture

Technologies often target subsets of the yield distribution

Examples from Crop Science Lit.: Barry et al. 2000; Dunwell 2000; Ellis et al. 2000; Badu-Apraku, Menkir and Lum 2007; De Bruin and Pederson 2008; Gosala, Wania and Kang 2009; Edgerton et al. 2012.

Some examples:

1. *Triple-stacked* seeds: increase resilience to pests and high winds (Edgerton *et al.* 2012)
2. *Racehorse* seeds: increase top-end yield under near-optimal conditions (Lauer and Hicks 2005)

Not likely to result in a shift of the mean

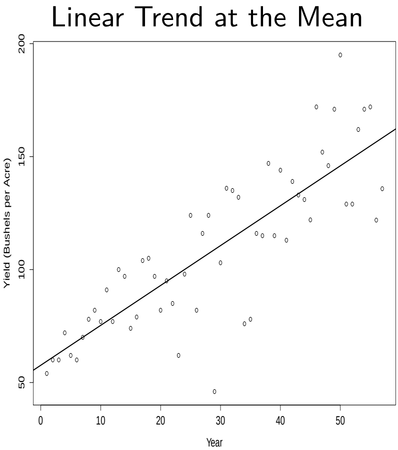
Measuring Technological Change in Agriculture

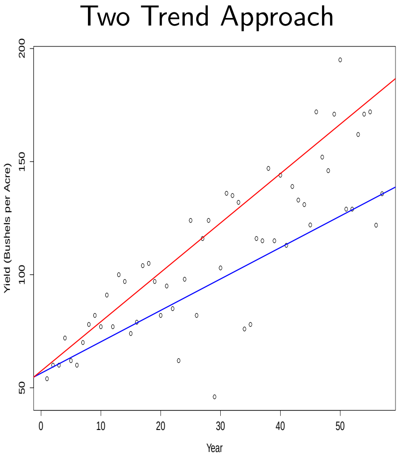
1. Possible that rates of technological change are different across different subsets of the yield distribution
   - i.e. top subset could increase faster than bottom subset, or *vice versa*
2. Technological change could also change the probability of different subsets occurring
   - i.e. ideally top subset would become more likely than than bottom subset

Neither would be captured by estimating a trend only at the mean (i.e. a shift of a location in the mean)

An Illustrative Example: Adams County, IL Corn

Estimated Technological Trend





Approaches from the Literature
Technological Trend

Some examples:

- Simple linear trend
- Piecewise linear splines (Skees & Reed 1986)
- Stochastic Kalman filter (Kaylen & Koroma 1991)
- ARIMA (Goodwin & Ker 1998)
- Polynomial trend (Just & Weninger 1999)
- Spatio-temporal approach (Ozaki & Silva 2009)

(But all these approaches estimate the trend at the mean)

Approaches from the Literature

Conditional Yield Density Models

Some examples:

- Normal (Botts & Boles 1958; Just & Weninger 1999)
- Lognormal (Day 1965)
- Gamma (Gallagher 1987)
- Beta (Nelson & Preckel 1989)
- **Mixture of two normals (Ker 1996)**
- Nonparametric kernel densities (Goodwin & Ker 1998)
- Semiparametric (Ker and Coble 2003)
- Logistic (Atwood, Shaik & Watts 2003)
- Weibull (Sherrick et al 2004)

(But all these approaches assume distribution constant over time)

Measuring Technological Change in Agriculture

Our approach:

- Empirical model to simultaneously estimate “states” and their parameters (which includes rate of technological change)
- States are weakly-identified subsets of the yield distribution
- Then we can:
  1. test for unique rates of technological change across states
  2. test to see if probability of states is constant over time

Highlights

- Estimate rate of technological change in two states ("upper state" and "lower state") using a mixture model
- Test to see if the rates of technological change are different
- Find **78%** of cases have statistically different rates of change
- Test to see if the probability of a state is constant but find inconclusive results (specification challenging)

Model Intuition

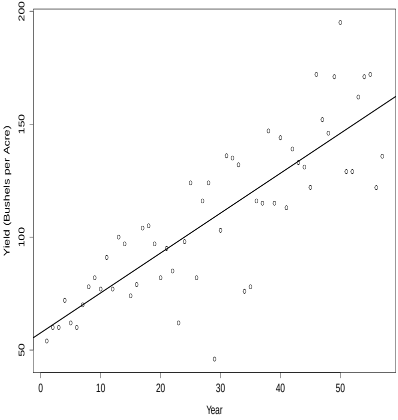
- Producer's output is determined by state of the world
- There are $J \in \mathbb{N}$ finite possible states
- Producer's output (i.e. yield) determined by a two-step process:
    1. Realized state $j \in J$ is determined by a random i.i.d. draw
    2. Realized yield $y_t \sim \phi(\theta_j \mid j)$ in another random i.i.d. draw
- Parameters θ_j may change over time (technological change)

In different states there are potentially different trajectories of technological change

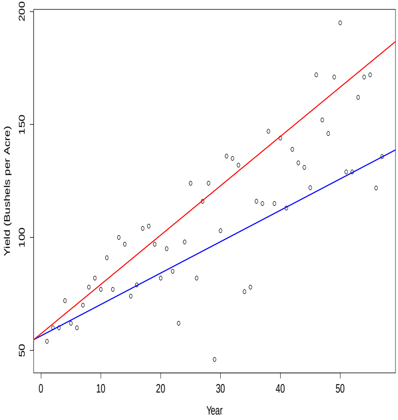
An Illustrative Example: Adams County, IL Corn

Estimated Technological Trend

Linear Trend at the Mean

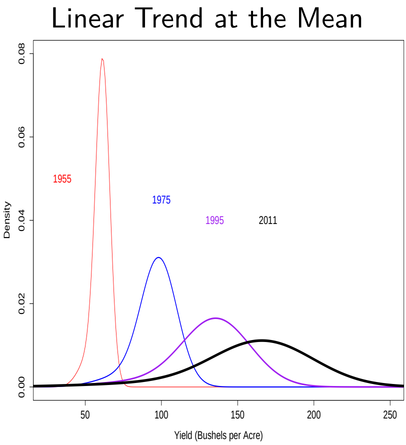


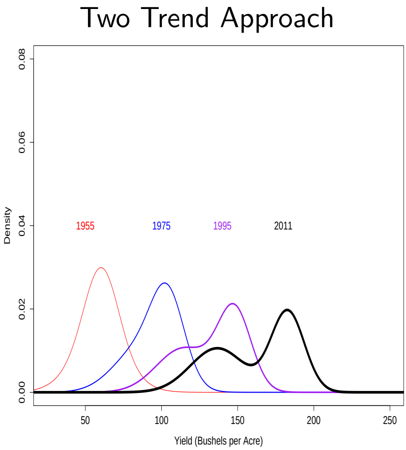
Two Trend Approach



An Illustrative Example: Adams County, IL Corn

Estimated Conditional Yield Densities





An Illustrative Example: Adams County, IL Corn

An Economic Application

Estimated Crop Insurance Premium Rates

	Coverage Level	
Method	75%	90%
Traditional	3.82%	6.54%
Mixture	0.70%	3.46%

- Traditional rates and two-trend rates are quite different
- Differences of this magnitude would have significant economic consequences for the actuarial soundness of a crop insurance program

Two-Trend Mixture Model

Model to be Estimated:

$$y_t \sim (1-\lambda)N(\alpha_\ell + \beta_\ell t, \sigma_\ell^2) + \lambda N(\alpha_u + \beta_u t, \sigma_u^2) \tag{1}$$

- y_t observed crop yields y over time t
- λ probability of the *upper state*
- α_ℓ intercept for *lower state* technological trend
- β_ℓ slope for *lower state* technological trend
- σ_ℓ^2 *lower state* homoscedastic component variance
- α_u intercept for *upper state* technological trend
- β_u slope for *upper state* technological trend
- σ_u^2 *upper state* homoscedastic component variance

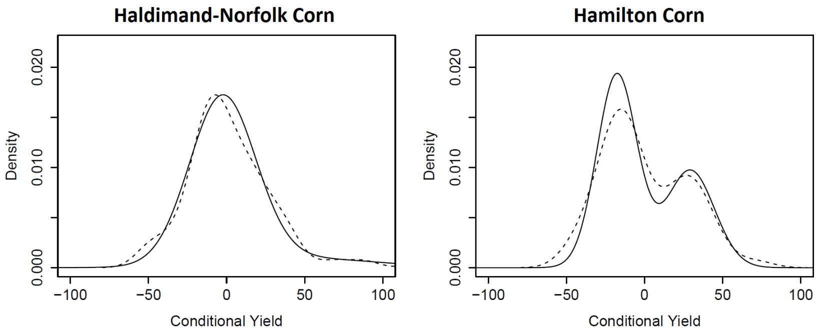
Normal Mixture Model

Why Choose Two Components?

- Mixture model of two normals is quite flexible and can accomodate:
  1. Symmetrical unimodal densities
  2. Skewed unimodal densities
  3. Bimodal densities
- Typically the literature considers only (1) and (2)
- Some examples with real data

Normal Mixture Model Fitting Examples: Corn

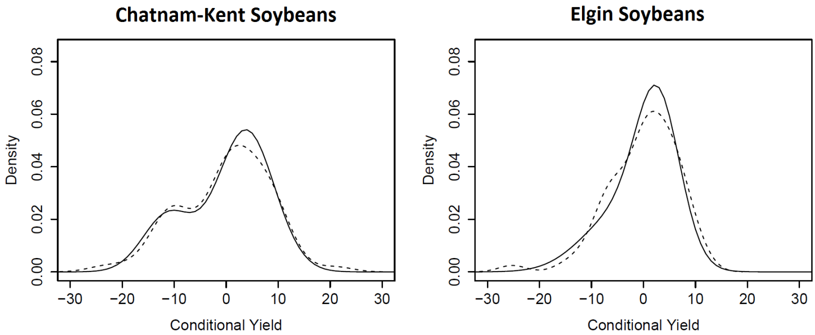
Estimated Conditional Crop Yield Densities



Full lines illustrate EM-estimated normal mixture model

Dashed lines illustrate nonparametric kernel density estimate for comparison

Normal Mixture Model Fitting Examples: Soybeans
Estimated Conditional Crop Yield Densities



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Normal Mixture Model Fitting Examples: Wheat

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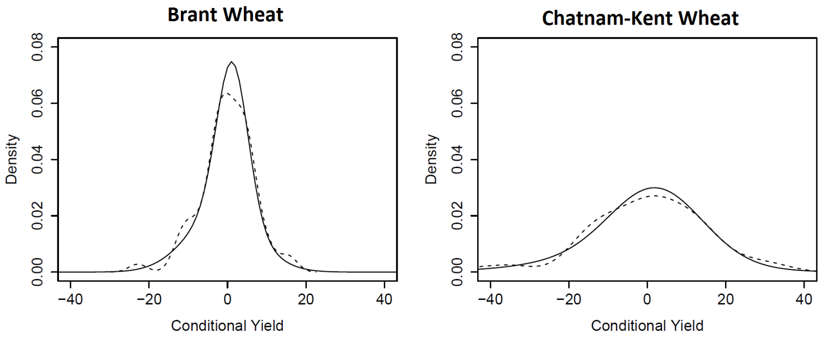

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Data: Two Caveats

1. Realized yields are a function of adopted technologies
   not necessarily set of possible technologies
   - Therefore our conclusions concern rate of *adopted* rather than *possible* technological change

2. Must use county-level data (farm-level data would be ideal)
   - Relevant for area-yield insurance programs (GRP, GRIP, GRIPH, proposed shallow loss programs)

Crop-county Combinations

Region	Source	Period	Corn	Soybean	Wheat
Ontario	OMAF	1949 - 2010	32	6	25
Illinois	NASS	1955 - 2011	97	97	-
Indiana	"	"	79	82	-
Iowa	"	"	99	98	-
Kansas	NASS	1968 - 2011	-	-	93
Nebraska	"	"	-	-	50
Texas	"	"	-	-	96
Total			307	283	264

- 854 total crop-county combinations
- All counties with incomplete yield histories excluded

Importance of Selected State-Crops

U.S. Data: Share and Rank of National Production

	Corn		Soybean		Wheat	
State	Share	Rank	Share	Rank	Share	Rank
Illinois	15.6%	2	13.7%	2		
Indiana	7.2%	5	7.8%	5		
Iowa	17.3%	1	15.4%	1		
Kansas					24.2%	1
Nebraska					4.3%	6
Texas					8.6%	2

In corresponding data set's most recent reporting year.

Ontario: three most important field crops (> \$2 billion in 2010)

Two Empirical Questions

Question

Is there a statistically significant difference between the rate of technological change in the upper and lower states?

Question

Is the probability of being in the upper state stable over time?

Operationalizing the Model

Maximum likelihood approach to incomplete data
(Dempster, Laird & Rubin, 1977)

- We want to know the parameters of each state
- Assume there exists an identity variable vector $\mathbb{Z}$ that identifies the states
- If we knew $\mathbb{Z}$ it would be easy to estimate θ_j
- However $\mathbb{Z}$ is latent and we only observe yields y_t
- Let $\gamma \in [0, 1]$ be a **weakly-assigned** estimate of $\mathbb{Z}$ called the “expectations vector”
- We can use y_t to estimate γ and the respective parameters of each state in an iterative algorithm (the EM algorithm)

Expectation-Maximization Algorithm

Overview of the EM Algorithm

- Name from its two steps
  - E Expectation Step
  - M Maximization Step
- Convergence problems of direct likelihood maximization with mixture models and therefore must use EM algorithm
- EM Algorithm is heuristic
  - parameter estimates improve at each iteration
- Limitation: may converge on local maxima

Expectation-Maximization Algorithm

The EM Algorithm

1. Expectation (E-)Step
    - Estimate the expectations
2. Maximization (M-)Step
    - Use expectations to analytically update parameter estimates

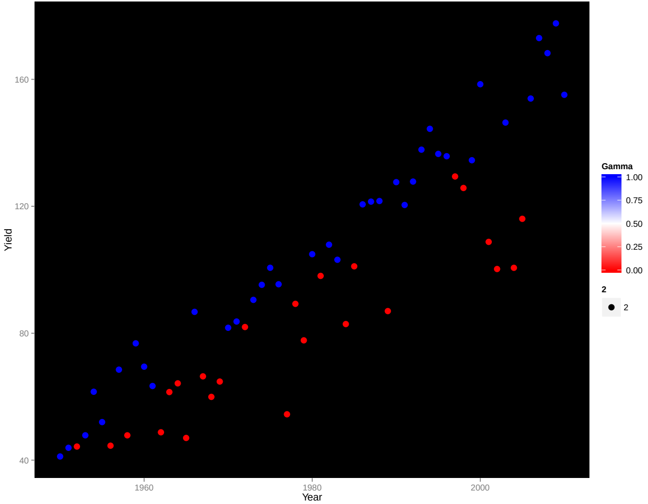
With updated parameter estimates repeat E-step to calculate new expectations vector, and so on, until convergence criteria are fulfilled

Expectation-Maximization Algorithm

A Closer Look at the E-Step

- γ is the vector of expectations calculated in the E-step
- λ is the scalar mean of γ
- Given current iteration's parameter estimates E-step calculates probability of being in the upper distribution
- Therefore "lower" and "upper" years are not chosen but relatively defined estimation parameters of the model (and hence the quotation marks)

A Closer Look at the E-Step



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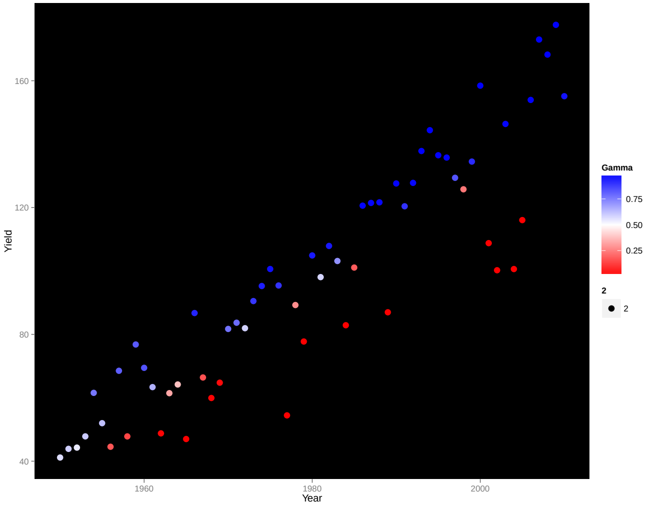

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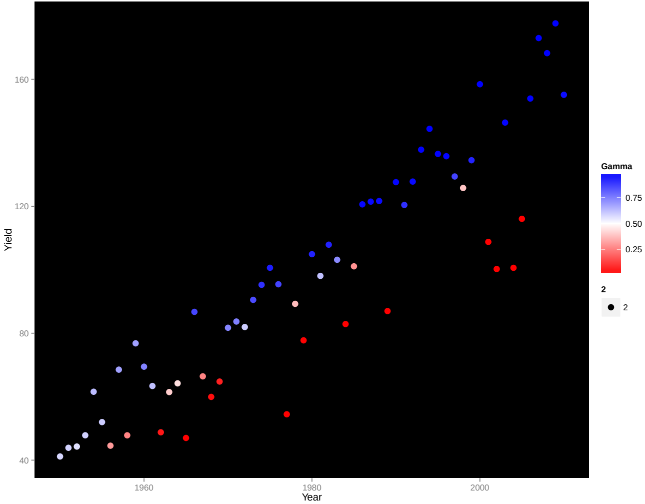

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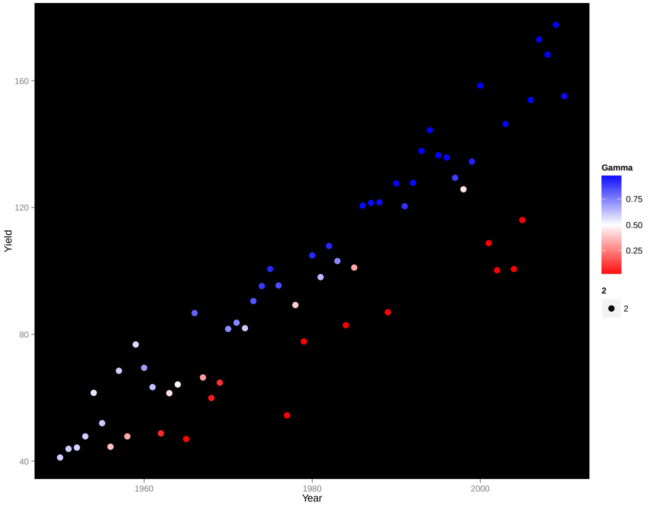

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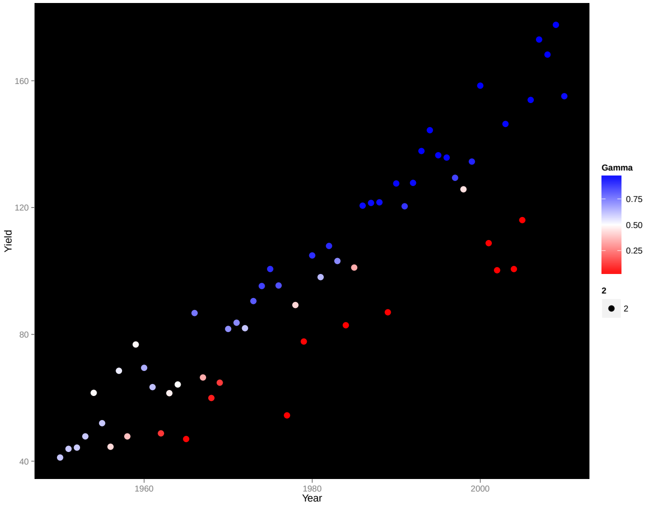

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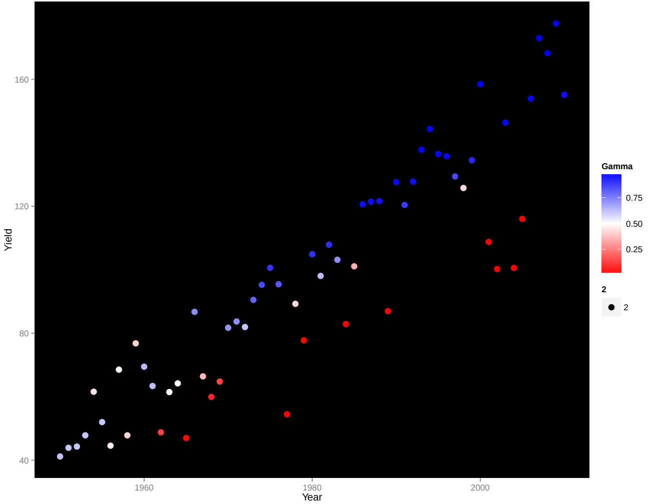

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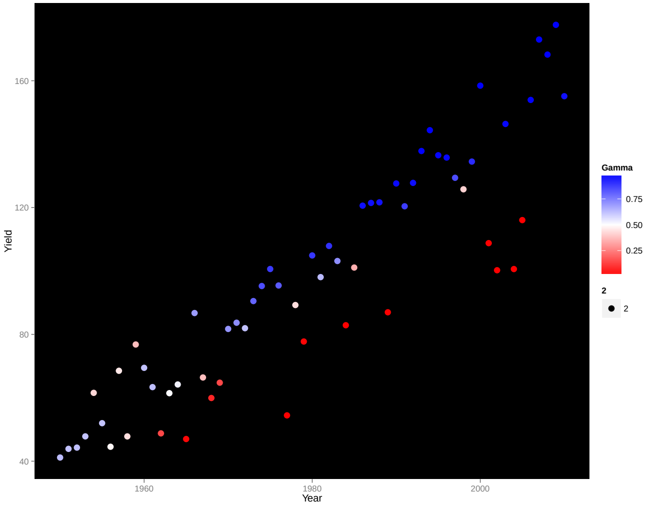

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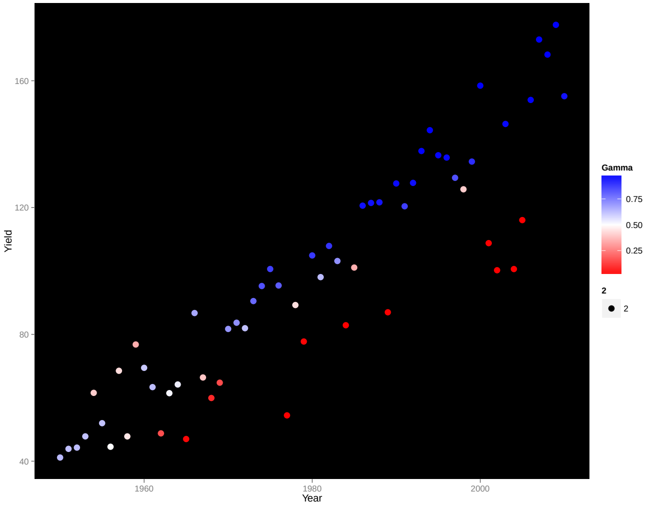
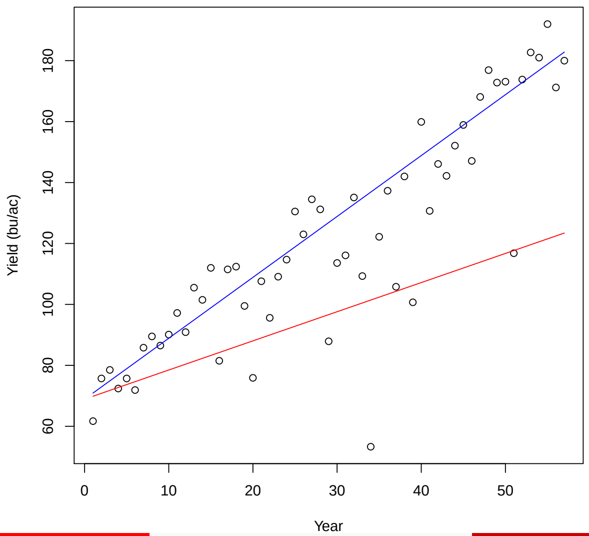


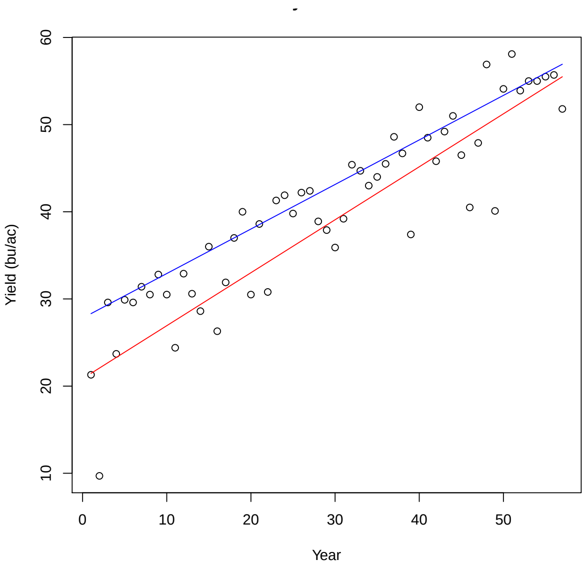
Representative Estimate

Clinton IA Corn



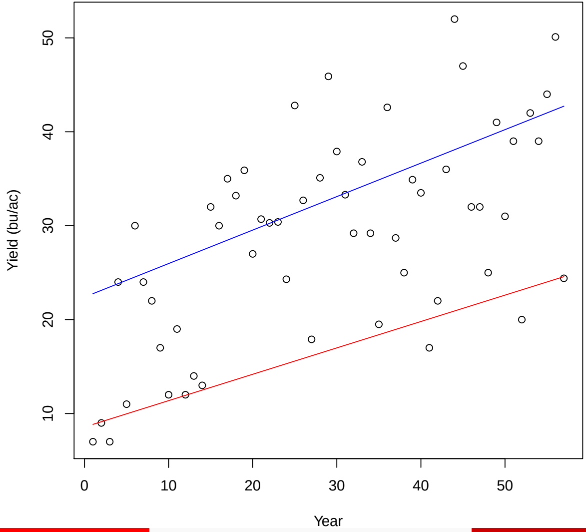
Atypical Estimate

Cherokee IA Soybean



Atypical Estimate

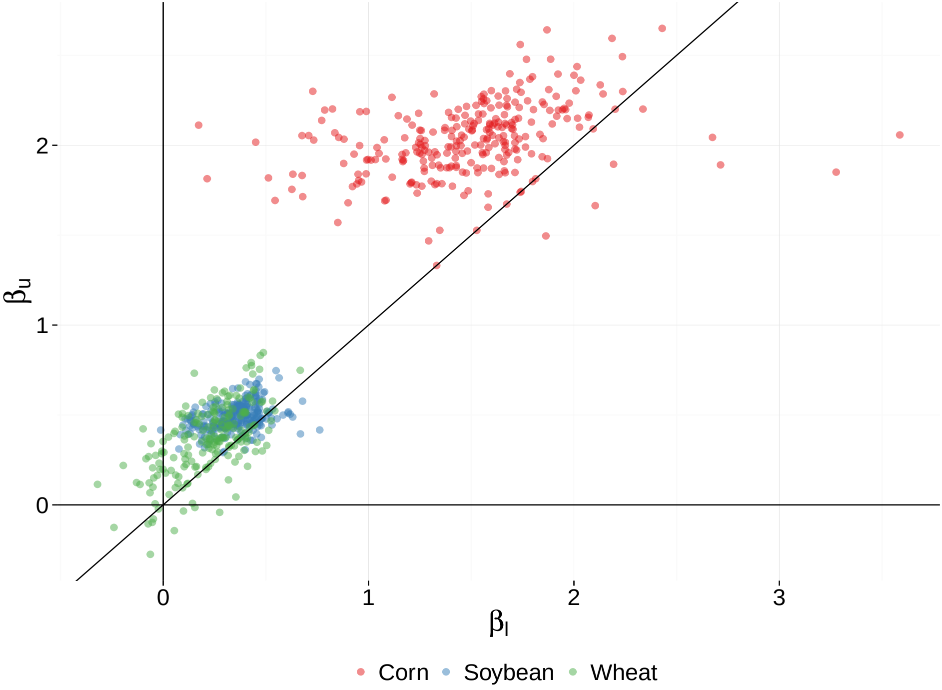
Hodgeman KS Wheat



Different Trends in Two States?

Evidence

- 8.6% have faster rate of technological change in *lower state*
- 4.6% have equal rate of technological change in *upper state*
- 81.5% *upper state* trend is greater 110% of *lower state* trend
- 68.4% *upper state* trend is greater 125% of *lower state* trend
- 37.9% *upper state* trend is greater 150% of *lower state* trend
- 16.7% *upper state* trend is **double** the *lower state* trend



βu
2
1
0
0
1
2
3
βl
Corn
Soybean
Wheat

Different Trends in Two States?

Hypothesis Test One:

$$H_o^1 : \beta_\ell = \beta_u$$
$$H_a^1 : \beta_\ell \neq \beta_u$$

Using likelihood ratio test.

Rejection rates (5% significance level):

Corn	Soybean	Wheat	Total
84.4%	82.7%	65.5%	78.0%

Majority **reject** equivalent rate of change in two states

Stable Probability of "Belonging to" Upper State?

Hypothesis Test Two:

Where δ is the estimated slope coefficient from a linear regression of $\gamma = h(t)$

$$H_o^2 : \delta = 0$$
$$H_a^2 : \delta \neq 0$$

Using a t-test with robust standard errors.

Rejection rates (5% significance level):

Corn	Soybean	Wheat	Total
10.8%	5.3%	6.0%	7.5%

Majority **fail to reject** stable expectations vector

Corn Hypothesis Rejection Rates (5% Significance Level)

	Number of Counties	Null Hypothesis One $\hat{\beta}_P = \hat{\beta}_R$	Null Hypothesis Two $\delta = 0$
Ontario	32	87.50%	0.00%
Illinois	97	81.40%	16.50%
Indiana	79	84.80%	15.20%
Iowa	99	85.90%	5.10%
Sub-total	307	84.36%	10.77%
Total	854	77.99%	7.49%

Note: H_o^1 evaluated using a likelihood ratio test. H_o^2 evaluated using a t-test with robust standard errors where δ is the estimated slope coefficient of a linear regression $\hat{\gamma}_i = f(t)$.

Soybean Hypothesis Rejection Rates (5% Sign. Level)

	Number of Counties	Null Hypothesis One $\hat{\beta}_P = \hat{\beta}_R$	Two $\delta = 0$
Ontario	6	100.00%	0.00%
Illinois	97	83.50%	4.10%
Indiana	82	80.50%	4.90%
Iowa	98	82.70%	7.10%
Sub-total	283	82.70%	5.28%
Total	854	77.99%	7.49%

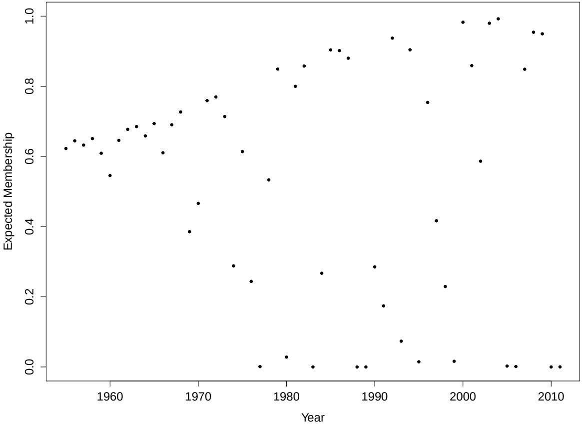
Note: H_o^1 evaluated using a likelihood ratio test. H_o^2 evaluated using a t-test with robust standard errors where δ is the estimated slope coefficient of a linear regression $\hat{\gamma}_i = f(t)$.

Wheat Hypothesis Rejection Rates (5% Significance Level)

	Number of Counties	Null Hypothesis One $\hat{\beta}_P = \hat{\beta}_R$	Two $\delta = 0$
Ontario	25	80.00%	20.00%
Kansas	93	79.60%	1.10%
Nebraska	50	56.00%	8.00%
Texas	96	53.10%	6.20%
Sub-total	264	65.53%	6.05%
Total	854	77.99%	7.49%

Note: H_o^1 evaluated using a likelihood ratio test. H_o^2 evaluated using a t-test with robust standard errors where δ is the estimated slope coefficient of a linear regression $\hat{\gamma}_i = f(t)$.

Stable Probability of "Belonging to" Upper State?



- Possible determinants of δ? (technology, weather, etc.)
- Might be (a) no effect or (b) no *net* effect

An Application: Crop Insurance Rates

Out-of-Sample Simulated Game

- Common technique in crop insurance literature for comparing two rate-setting techniques (Ker & McGowan 2000; Ker & Coble 2003; Racine & Ker 2006; Harri *et al.* 2011.)
- Out-of-sample: mimics real life
- If new method has no advantage, will not perform better

Number of "winning" states:

Corn	Soybean	Wheat	Total
4/6 (1)	4/6 (0)	5/6 (4)	13/18 (5)

Statistically significant wins at the 5% level in brackets

An Application: Crop Insurance Rates

Some Minor Caveats

- Comparison at lower-end of the density tail only
- Not quite an apples-to-apples comparison
  - Two component trend method does not exhibit heteroscedasticity

- Two trend method seems to performs better
- Rate improvement in 13 of 18 crop-state combinations
- Statistically significant improvement in 5 of 18 states
- No statistically significant wins in opposite direction
- Higher bar to exceed than earlier in-sample likelihood-ratio test - power of the test is weaker

Out-of-Sample Rating Game Results: Corn

Set	Coverage Level	Retained by Private	Psuedo Loss Ratio: Private	Psuedo Loss Ratio: Government	*p*-value	% Payo
IL	75%	85.9%	0.092	0.026	0.787	3.0%
	90%	87.8%	0.287	0.465	**0.012**	18.6%
IN	75%	81.1%	0.164	0.134	0.604	3.7%
	90%	82.4%	0.395	0.434	0.373	19.8%
IA	75%	83.9%	0.357	0.409	0.361	6.6%
	90%	86.8%	0.406	0.444	0.291	12.2%

Note: Winner and $p < \mathbf{0.05}$ or $p < \mathbf{0.95}$

Out-of-Sample Rating Game Results: Soybean

Set	Coverage Level	Retained by Private	Psuedo Loss Ratio Private	Psuedo Loss Ratio Government	*p*-value	% Payo
IL	75%	77.7%	0.366	0.374	0.431	3.0%
	90%	67.4%	0.540	0.474	0.695	12.9%
IN	75%	86.9%	0.257	0.258	0.479	3.4%
	90%	78.4%	0.611	0.746	0.201	19.6%
IA	75%	80.6%	0.809	0.467	0.757	6.1%
	90%	78.7%	0.751	0.911	0.076	16.1%

Note: Winner and $p <$ **0.05** or $p <$ **0.95**

Out-of-Sample Rating Game Results: Wheat

	Coverage	Retained	Psuedo Loss Ratio			
Set	Level	by Private	Private	Government	p-value	% Payo
KS	75%	52.6%	1.297	1.921	**0.023**	18.5%
	90%	41.9%	1.268	1.399	0.217	33.0%
NE	75%	40.8%	0.309	0.747	0.070	5.3%
	90%	45.3%	0.652	0.611	0.587	19.8%
TX	75%	73.5%	0.957	2.096	**0.001**	19.5%
	90%	69.1%	1.112	1.593	**0.001**	43.8%

Note: Winner and $p < \mathbf{0.05}$ or $p < \mathbf{0.95}$

Summary

- Crop yields are important measuring stick of agricultural productivity
- Crop science literature suggests yields have distinct subsets of the yield distribution—are the rates of technological change equal across these subsets?
- We propose an empirical model that explicitly allows for unique trends in two states

Conclusions

1. Trajectory of technological change
   - different trajectories in different states
   - statistically significant difference in 78% of cases
   - $>$ 85% slower rate of technological change in *lower state*
2. Inconclusive results w.r.t. stable probability of the *upper state*
3. Mixture model opens the door for a lot of interesting questions. . .
4. Results consistent with plant science research expenditures (corn versus beans, racehorse versus suboptimal)
5. Results consistent with stylized facts regarding heteroscedasticity
6. Results suggest little effect of climate change.
7. Results inconsistent with what you would find looking at moments from single technology estimation
8. Results are fairly robust within a crop

Going Forward

- Can we isolate the underlying cause(s) of different trends in the two states?
- How different are the results at the farm-level?
  - Trial farm project in initial stages
- What are the determinants of yields "belonging to" the *upper state*?
  - What climatic/weather conditions can we isolate as important?

Thank You

Questions?

Funding for this research was generously provided by the Ontario Ministry of Food and Agriculture (OMAF) and the Institute for the Advanced Study of Food and Agricultural Policy

Operationalizing the Model

Maximum likelihood approach to incomplete data
(Dempster, Laird & Rubin, 1977)

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Corn	307	84.36%	10.77%
Soybean	283	82.70%	5.28%
Wheat	264	65.53%	6.05%
Total	**854**	**77.99%**	**7.49%**

Note: H_o^1 evaluated using a likelihood ratio test. H_o^2 evaluated using a t-test with robust standard errors where δ is the estimated slope coefficient of a linear regression $\hat{\gamma}_i = f(t)$.

Corn Hypothesis Rejection Rates (5% Significance Level)

	Number of Counties	Null Hypothesis One $\hat{\beta}_P = \hat{\beta}_R$	Two $\delta = 0$
Ontario	32	87.50%	0.00%
Illinois	97	81.40%	16.50%
Indiana	79	84.80%	15.20%
Iowa	99	85.90%	5.10%
Sub-total	307	84.36%	10.77%
Total	854	77.99%	7.49%

Note: H_o^1 evaluated using a likelihood ratio test. H_o^2 evaluated using a t-test with robust standard errors where δ is the estimated slope coefficient of a linear regression $\hat{\gamma}_i = f(t)$.

Soybean Hypothesis Rejection Rates (5% Sign. Level)

	Number of Counties	Null Hypothesis One $\hat{\beta}_P = \hat{\beta}_R$	Null Hypothesis Two $\delta = 0$
Ontario	6	100.00%	0.00%
Illinois	97	83.50%	4.10%
Indiana	82	80.50%	4.90%
Iowa	98	82.70%	7.10%
Sub-total	283	82.70%	5.28%
Total	854	77.99%	7.49%

Note: H_o^1 evaluated using a likelihood ratio test. H_o^2 evaluated using a t-test with robust standard errors where δ is the estimated slope coefficient of a linear regression $\hat{\gamma}_i = f(t)$.

Wheat Hypothesis Rejection Rates (5% Significance Level)

	Number of Counties	Null Hypothesis One $\hat{\beta}_P = \hat{\beta}_R$	Null Hypothesis Two $\delta = 0$
Ontario	25	80.00%	20.00%
Kansas	93	79.60%	1.10%
Nebraska	50	56.00%	8.00%
Texas	96	53.10%	6.20%
Sub-total	264	65.53%	6.05%
Total	854	77.99%	7.49%

Note: H_o^1 evaluated using a likelihood ratio test. H_o^2 evaluated using a t-test with robust standard errors where δ is the estimated slope coefficient of a linear regression $\hat{\gamma}_i = f(t)$.

An Application: Crop Insurance Rates

Out-of-Sample Simulated Game

- Common technique in crop insurance literature for comparing two rate-setting techniques (Ker & McGowan 2000; Ker & Coble 2003; Racine & Ker 2006; Harri *et al.* 2011.)
- Out-of-sample: mimics real life
- If new method has no advantage, will not perform better

Number of "winning" states:

Corn	Soybean	Wheat	Total
4/6 (1)	4/6 (0)	5/6 (4)	13/18 (5)

Statistically significant wins at the 5% level in brackets

An Application: Crop Insurance Rates

Some Minor Caveats

- Comparison at lower-end of the density tail
- Does not reflect ability of the model to fit all the data
- *And* not quite an apples-to-apples comparison
  - Two component trend method more constrained in its heteroscedasticity treatment (minor disadvantage)

An Application: Crop Insurance Rates

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  - Two component trend method more constrained in its heteroscedasticity treatment (minor disadvantage)

- Two trend method performs better (despite minor disadvantage)
- Rate improvement in 13 of 18 crop-state combinations
- Statistically significant improvement in 5 of 18 states
- No statistically significant wins in opposite direction
- Higher bar to exceed than earlier in-sample likelihood-ratio test

Out-of-Sample Rating Game Results: Corn

Set	Coverage Level	Retained by Private	Psuedo Loss Ratio Private	Psuedo Loss Ratio Government	p-value	% Payo
IL	75%	85.9%	0.092	0.026	0.787	3.0%
	90%	87.8%	0.287	0.465	**0.012**	18.6%
IN	75%	81.1%	0.164	0.134	0.604	3.7%
	90%	82.4%	0.395	0.434	0.373	19.8%
IA	75%	83.9%	0.357	0.409	0.361	6.6%
	90%	86.8%	0.406	0.444	0.291	12.2%

Note: Winner and $p < \mathbf{0.05}$ or $p < \mathbf{0.95}$

Out-of-Sample Rating Game Results: Soybean

Set	Coverage Level	Retained by Private	Psuedo Loss Ratio: Private	Psuedo Loss Ratio: Government	p-value	% Payo
IL	75%	77.7%	0.366	0.374	0.431	3.0%
	90%	67.4%	0.540	0.474	0.695	12.9%
IN	75%	86.9%	0.257	0.258	0.479	3.4%
	90%	78.4%	0.611	0.746	0.201	19.6%
IA	75%	80.6%	0.809	0.467	0.757	6.1%
	90%	78.7%	0.751	0.911	0.076	16.1%

Note: Winner and $p <$ **0.05** or $p <$ **0.95**

Out-of-Sample Rating Game Results: Wheat

	Coverage	Retained	Psuedo Loss Ratio			
Set	Level	by Private	Private	Government	p-value	% Payo
KS	75%	52.6%	1.297	1.921	**0.023**	18.5%
	90%	41.9%	1.268	1.399	0.217	33.0%
NE	75%	40.8%	0.309	0.747	0.070	5.3%
	90%	45.3%	0.652	0.611	0.587	19.8%
TX	75%	73.5%	0.957	2.096	**0.001**	19.5%
	90%	69.1%	1.112	1.593	**0.001**	43.8%

Note: Winner and $p <$ **0.05** or $p <$ **0.95**