Estimation for County Level Cropland Cash Rental Rates

Emily Berg¹, Will Cecere², Malay Ghosh³

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¹Iowa State University, ²Westat, ³University of Florida

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Outline

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 - NASS annual Cash Rent Survey
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 - Auxiliary information
- General bivariate model for two time means
 - Decomposition as average (level) and difference (change)
 - Add predictor of average to one half predictor of difference
- Specific procedures for Cash Rent Survey
 - Estimation of differences
 - Estimation of sampling variances
 - Definitions of covariates
- Results for 2011
- Simulation
- Discussion

Cash Rental Rates

- Cropland or pastureland rented in \$/acre
 - Useful to producers, policy-makers, researchers
 - Farm Service Agency uses cash rental rates for guidance in calculating rates for the Conservation Reserve Program
- 2008 Farm Bill requires annual cash rent survey
 - Land uses: irrigated cropland, nonirrigated cropland, pasture
 - Counties with at least 20,000 acres in cropland or pastureland
- NASS Annual Cash Rent Survey (2009-2012)
 - Stratified sample
 - pprox 224,000 operations each year
 - Direct estimators weighted sums

w
$$\propto [({\sf select. prob.})({\sf resp. prob.})]^{-1}$$

Jackknife variance estimator

Cash Rental Rates: Cash Rent Survey





- Direct estimators for 2011 and 2010 correlated
- Wide range in county sample sizes and estimated CVs

Objectives

- Efficient estimates of average cash rental rates at the county level
 - Irrigated, nonirrigated, permanent pasture
 - $\bullet~$ Counties with \geq 20,000 acres of cropland or pastureland
- Mean squared error estimators
- Computational simplicity
- Data
 - Survey data for 2 years t 1, t (eg. 2010, 2011)
 - Focus on South Dakota (SD) and Florida (FL) for this presentation
 - Auxiliary data

- 2007 Census of Agriculture
 - Total value of agricultural production in a county
- NASS published county yields from 2005-2009
 - Yield indexes: irrigated, nonirrigated, total, hay
- National Commodity Crop Productivity Indexes (NCCPI) (Developed by the Natural Resources Conservation Service)
 - Three indexes: corn, cotton, wheat
 - Reflect the productivity of the soil for growing nonirrigated crops in different climates
- Covariates constant across two consecutive years
 - Information about *level*
 - Only provide information about *change* to the extent that level and change are correlated

Bivariate Model: Relationships between Level and Change

• Average cash rent/acre for time t is a sum of the average and half of the difference

$$\begin{array}{l} \theta_{i,t} = \mbox{ true avg. cash rent/acre, county } i \mbox{ time } t \\ \theta_{i,t} = \theta_i + 0.5\Delta_i \\ \theta_i = 0.5(\theta_{i,t-1} + \theta_{i,t}), \Delta_i = \theta_{i,t} - \theta_{i,t-1} \end{array}$$

 We can construct a predictor of a time t mean by adding a predictor of an average to half of a predictor of a difference.

Bivariate Model: Relationships between Level and Change

٩	$\widehat{y}_{i,t} = ext{ direct est. of } heta_{i,t}$
٩	$V\{\widehat{y}_{i,t}\} = V\{\widehat{y}_{i,t-1}\}$
	implies $\widehat{y}_{i,t} - \widehat{y}_{i,t-1}$ and
	$0.5(\widehat{y}_{i,t} + \widehat{y}_{i,t-1})$ are
	uncorrelated

	State	Use	$C\{n_{11}, n_{10}\}$	$C{(Avg,Diff)}$	Т		
SD Nir 0.94		0.94	0.37	3.18			
	FL Nir 0.96		-0.14	-0.83			
	SD	Pas	0.79	0.17	1.34		
	FL	Pas	0.90	0.08	0.63		
SD Irr 0.86				0.41	2.33		
	FL Irr 0.85 0.24 1						
	T = Pitman-Morgan test statistic of						
	$H_o: Cor\{(Avg,Diff)\} = 0.$						

• A *working* assumption of constant variance for two time points appears reasonable for Cash Rent Survey data.

Bivariate Model: Decomposition as Level and Change

• Univariate models for average and difference (Fay and Herriot, 1979)

 $\begin{array}{ll} & \underbrace{\mathsf{Average}} & \underbrace{\mathsf{Difference}} \\ \widehat{y}_i = 0.5(\widehat{y}_{i,t} + \widehat{y}_{i,t-1}) & \widehat{d}_i = \text{ direct estimate of diff.} \\ = \theta_i + e_i, \theta_i = \mathbf{x}'_i \mathbf{\beta} + u_i & = \Delta_i + \eta_i, \Delta_i = \mathbf{z}'_i \mathbf{\beta}_d + v_i \\ (u_i, e_i)' \sim [\mathbf{0}, \operatorname{diag}(\sigma_u^2, \sigma_{ei,avg}^2)] & (v_i, \eta_i)' \sim [\mathbf{0}, \operatorname{diag}(\sigma_v^2, \sigma_{\eta i, diff}^2)] \end{array}$

 \bullet Assume estimates of $\sigma^2_{ei,avg}$ and $\sigma^2_{\eta i,diff}$ are available.



- Estimated generalized least squares estimators of model parameters
 - Modification of Wang, Fuller, and Qu (2008)
 - Positive estimator of σ_u^2 and σ_v^2

Working assumption: $C\{u_i, v_i\} = 0$ and $C\{e_i, \eta_i\} = 0$

- Estimator of optimal linear predictor if errors in average and difference are uncorrelated
- Unbiased but possibly inefficient if working model not true

Bivariate Model: MSE Estimators

• Working assumption that average and difference uncorrelated

$$\widehat{MSE}_{i,w} = \widehat{MSE}(\widehat{\theta}_i) + 0.25\widehat{MSE}(\widehat{\Delta}_i)$$
$$\widehat{MSE}(\widehat{\theta}_i) = \widehat{\gamma}_i \widehat{\sigma}_{ei,avg}^2 + \widehat{g}_{2i,a} + 2\widehat{g}_{3i,a}$$
$$\widehat{MSE}(\widehat{\Delta}_i) = \widehat{\lambda}_i \widehat{\sigma}_{\eta i,diff}^2 + \widehat{g}_{2i,d} + 2\widehat{g}_{3i,d}$$

• $\widehat{g}_{2i,a}$ and $\widehat{g}_{3i,a}$ for estimation of β and σ_u^2 (Prasad and Rao, 1990) • $\widehat{MSE}_{i,w}$ biased if average and difference correlated

• Relax assumption that sampling errors in avg. and diff. uncorrelated

$$\begin{split} \widehat{MSE}_{i,t} &= \widehat{g}_{1it,cor} + \widehat{g}_{2i,a} + 2\widehat{g}_{3i,a} + 0.25(\widehat{g}_{2i,d} + 2\widehat{g}_{3i,d}) \\ \widehat{g}_{1it,cor} &= (1 - \widehat{\gamma}_{i,avg})^2 \widehat{\sigma}_u^2 + 0.25(1 - \widehat{\gamma}_{i,diff})^2 \widehat{\sigma}_v^2 \\ &+ (1, 0.5) \mathsf{diag}(\widehat{\gamma}_{i,avg}, \widehat{\gamma}_{i,diff}) \widehat{\Sigma}_{e\eta,i} \mathsf{diag}(\widehat{\gamma}_{i,avg}, \widehat{\gamma}_{i,diff})(1, 0.5)' \\ \widehat{\Sigma}_{e\eta,i} &= \widehat{\mathsf{Cov}}\{(e_i, \eta_i)'\} \end{split}$$

Specific Procedures for Cash Rent Survey

- Estimation of differences
- ② Estimation of sampling variances
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Cash Rent Specifics: Estimation of Differences

Unit Level Cash Rental Rates



- Responses for units in both survey years are correlated
- Variance of difference decreases as acres increase
- Outliers relative to normality
 - Eg. FL irrigated, unit-level differences can exceed 3 \times SD of differences

Cash Rent Specifics: Estimation of Differences

• Convex combination of $\hat{y}_{i,t} - \hat{y}_{i,t-1}$ and a weighted average of the difference for respondents in both time points

$$\begin{aligned} \widehat{d}_i &= \alpha_i \widehat{y}_{di} + (1 - \alpha_i) \overline{y}_{di} \\ \widehat{y}_{di} &= \widehat{y}_{i,t} - \widehat{y}_{i,t-1}, \\ \overline{y}_{di} &= \left(\sum_{j=1}^{n_{it,t-1}} d_{ij} a_{ij}\right) \left(\sum_{j=1}^{n_{it,t-1}} a_{ij}\right)^{-1} \end{aligned}$$

- j = unit in county i, $n_{it,t-1} =$ number in both years
- α_i optimal if sample sizes and variances for two time points equal
- $d_{ij} =$ unit-level difference after modification to outliers
- $a_{ij} =$ average acres rented

Cash Rent Specifics: Estimation of Sampling Variances

Jackknife variances

- Undefined for sample size < 2
- Large variances for small sample sizes
 - Avg. 2010 sample sizes between 2 and 60 (roughly)
- Correlated with direct estimators of means
 - Correlation between jackknife s.d. and $\widehat{y}_{i,2011}$ between 0.20 and 0.85

Implication

• Predictor undefined for sample size of 1

• Large prediction variance

• Biased GLS estimators

Cash Rent Specifics: Estimation of Sampling Variances

- Hierarchical model for sampling variances
 - n_{it} =sample size for county i and year t, $n_{it} > 1$
 - $n_{it}^{-1}(\sigma_{ei,t}^2, S_{it}^2) = ($ true sampling variance, jackknife estimator)

$$\begin{aligned} \frac{(n_{it}-1)S_{it}^2}{\sigma_{ei,t}^2} &| \sigma_{ei,t}^2 \sim \chi^2_{(n_{it}-1)}, \quad \frac{1}{\sigma_{ei,t}^2} \stackrel{d}{=} \frac{1}{\sigma_{0it}^2 \nu} X, \quad X \sim \chi^2_{\nu}, \\ E[S_{it}^2] &= \sigma_{0it}^2 = (\mu_{it}^2)\alpha \\ (\mu_{it-1}, \mu_{it}) &= (\mathbf{x}'_i \boldsymbol{\beta} - 0.5 \mathbf{z}_i \Delta_i, \mathbf{x}'_i \boldsymbol{\beta} + 0.5 \mathbf{z}_i \Delta_i) \end{aligned}$$

- Method of moments estimators: $\widehat{\alpha}$, $\widehat{\nu}$
- Estimator of sampling variance for county i and year t

$$\begin{split} \widehat{V}_{ei,t} &= n_{it}^{-1} E[\sigma_{ei,t}^2 \,|\, \widehat{\nu}, \widehat{\alpha}, S_{it}^2, \widehat{\mu}_{it}] = \frac{d_{it}^*}{d_{it}^* - 2} \sigma_{it}^{2*}, \\ d_{it}^* &= \widehat{\nu} + n_{it}, \quad \sigma_{it}^{2*} = \frac{\widehat{\nu}}{\widehat{\nu} + n_{it}} \widehat{\alpha} \widehat{\mu}_{it}^2 + \frac{n_{it}}{\widehat{\nu} + n_{it}} S_{it}^2 \end{split}$$

Cash Rent Specifics: Definitions of Covariates

• Correlations between \widehat{y}_i and Auxiliary Variables for SD

	Total Value	Yield		<u>NCCPI</u>	
Land Use	of Production	Total	Hay	Corn	Wheat
Nonirrigated	0.66	0.93	0.88	0.89	0.24
Pasture	0.68	0.86	0.92	0.85	0.35
Irrigated	0.32	0.66	0.60	0.64	0.16

Challenges

- Availability and nature of relationships vary by state and land use
- Colinearity among covariates
 - Eg. Cor(Hay Yield, Total Yield) for SD is 0.89
- Negative predicted values in the model for the average are possible.

Cash Rent Specifics: Definitions of Covariates

Univariate Covariate - Index of Productivity: x_i^*

- Linear combination of auxiliary variables
- Scaled to be strictly positive and have similar mean and variance as cash rental rate
- Little loss of information
 - For nonirrigated cropland for SD, R^2 of model with five covariates is 0.89, and R^2 of model with univariate covariate index is 0.83.

Cash Rent Specifics: Definitions of Covariates

Avgerage vs. Index of Productivity SD Nonirrigated



Xstar

• Segmented regression for average

$$\begin{aligned} \boldsymbol{x}_{i} &= (1, x_{i}^{*}, x_{i,1}^{*}, x_{i,2}^{*}) \\ x_{i,1}^{*} &= (x_{i}^{*} - x_{(m/3)}^{*}) I[x_{i}^{*} > x_{(m/3)}^{*}] \\ x_{i,2}^{*} &= (x_{i}^{*} - x_{(2m/3)}^{*}) I[x_{i}^{*} > x_{(2m/3)}^{*}] \end{aligned}$$

- Coefficient $\beta = (\beta_0, \beta_1, \beta_2, \beta_3)$
- Restrict estimates to ensure positive predicted value
- $\hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3 < 0, \rightarrow \text{ set } \hat{\beta}_3 = 0$ - $\hat{\beta}_1 + \hat{\beta}_2 < 0, \rightarrow \hat{\beta}_2 = 0$
- Covariate for difference

$$\boldsymbol{z}_i = (1, x_i^*)$$

Nonlinear relationship

Results for 2011 Cash Rent Survey

- Separate models for different states and land uses
- Benchmark to state level estimates (Ghosh and Steorts, 2012)
- Compare to predictor based on univariate area-level model for one time point

	Nonirrigated		<u>Pasture</u>		Irrigated	
	$\widehat{ heta}_{biv}$	$\widehat{ heta}_{uni}$	$\widehat{ heta}_{biv}$	$\widehat{ heta}_{uni}$	$\widehat{ heta}_{biv}$	$\widehat{ heta}_{uni}$
SD	0.62	0.89	0.60	0.82	0.58	0.85
FL	0.86	0.95	0.70	0.83	0.61	0.86

 Medians of ratios of estimated MSEs of bivariate (biv) and univariate (uni) predictors to estimated variances of direct estimators. • Medians of estimated CVs (percent) for bivariate predictors

State	Nonirrigated	Irrigated	Pasture
SD	5.11	6.27	11.26
FL	11.40	17.80	20.28

Results for 2011 Cash Rent Survey

• Standardized residuals for SD nonirrigated cropland

$$r_{i,avg} = rac{\widehat{y}_{i,avg} - \boldsymbol{x}_i' \widehat{\boldsymbol{eta}}}{\sqrt{\widehat{\sigma}_u^2 + \widehat{\sigma}_{ei,avg}^2}}, \quad r_{i,diff} = rac{\widehat{d}_i - \boldsymbol{z}_i' \widehat{\boldsymbol{eta}}_d}{\sqrt{\widehat{\sigma}_v^2 + \widehat{\sigma}_{\eta i,diff}^2}}$$



xβ

 $x_{\rm dr}\hat{\beta}_{\rm dr}$

Simulation

Population means

$$(\theta_{i1}, \theta_{i2})' \sim \mathsf{N}\left[(\mu_{i1}, \mu_{i2})', \boldsymbol{\Sigma}_{uu}\right], \quad \boldsymbol{\Sigma}_{uu} = \sigma_u^2 \begin{pmatrix} 1 & \rho_u \\ \rho_u & 1 \end{pmatrix}$$

Unit-level data

$$\begin{split} (y_{ij1},y_{ij2})' &\sim \mathsf{N}\left[(\theta_{i1},\theta_{i2})',\boldsymbol{\Sigma}_{ee}\right], \quad j=1,\ldots,n_{i12} \\ y_{ij1} &\sim \mathsf{N}(\theta_{i1},\sigma_{ei}^2), j=n_{i12}+1,\ldots,n_{i12}+n_{i11} \\ y_{ij2} &\sim \mathsf{N}(\theta_{i2},\sigma_{ei}^2), j=n_{i12}+n_{i11}+1,\ldots,n_{i22} \\ \boldsymbol{\Sigma}_{eei} &= \mathsf{diag}(\sigma_{ei,1},\sigma_{ei,2}) \begin{pmatrix} 1 & \rho_e \\ \rho_e & 1 \end{pmatrix} \mathsf{diag}(\sigma_{ei,1},\sigma_{ei,2}). \end{split}$$

- Parameter values based on SD nonirrigated cropland
- Model 1: $\sigma_{ei,1} = \sigma_{ei,2}$, $n_{i11} = n_{i22}$
- Model 2: $\sigma_{ei,1} \neq \sigma_{ei,2}$, $n_{i11} \neq n_{i22}$

Four predictors

Predictor	Definition	Covariates	Bivariate
$\widehat{y}_{i,2}$	sample mean for $t = 2$	No	No
$\widehat{ heta}_{i,ad}$	$\widehat{y}_i + 0.5\widehat{d}_i$	No	Yes
$\widehat{ heta}_{i,2}$	area-level model for $t=2$	Yes	No
$\widehat{ heta}_{i,biv}$	proposed predictor	Yes	Yes

• $\hat{\theta}_{i,ad}$ illustrates gain (if any) due to estimating change as a weighted average of the difference between the direct estimators and the weighted average of the differences for paired observations.

- Model 1 equal sampling error variances for two time points
- Model 2 unequal sampling error variances for two time points

	\widehat{y}_{i2}	$\widehat{ heta}_{i,ad}$	$\widehat{ heta}_{i2}$
Model 1	1.17	1.05	1.12
Model 2	1.28	1.14	1.14

• Medians of ratios of Monte Carlo (MC) MSEs of alternative predictors to MC MSEs of $\widehat{\theta}_{i,biv}$

Simulation

- MC properties of MSE estimators
 - $\widehat{MSE}_{i,w}$: working model that sampling variances for two time points equal
 - $\widehat{MSE}_{i,2}$: allows unequal sampling variances in leading term

MSE	Model 1 (Equal var.)		l var.) Model 2 (Unequal var.)	
Estimator	Rel. Bias	Cov. of 95% Cl	Rel. Bias	Cov. of 95% CI
$\widehat{MSE}_{i,w}$	-1.13	0.95	-8.30	0.94
$\widehat{MSE}_{i,2}$	-0.22	0.95	-2.97	0.94

- Medians of MC relative biases of MSE estimators
- MC coverages of normal theory confidence intervals (CI) with nominal coverage 0.95

- Combine predictors based on separate univariate area-level models for averages and differences
- Incorporates data from previous year and covariates
- Computationally simple
- Incorporates survey weights
- Does not rely on normality of unit-level data

Discussion: Possible Improvements

- Explore data for additional sources of structure (eg., spatial relationships, more than two time points, correlations between land uses)
- Integrate estimators of differences and sampling variances into the statistical model
- Formalize covariate selection
- Account for estimation of sampling variances, adjustments to outliers, and benchmarking in MSE estimation
- Directly consider nonsampling errors (eg., nonresponse, definitions of pasture, effects of arms-length transactiions)

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