Dynamic Discrete Choice Estimation of Agricultural Land Use

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Overview

Applied question

- What are the effects of biofuels policy?

Methodological issue

- How to estimate long-run elasticities of crop supply?

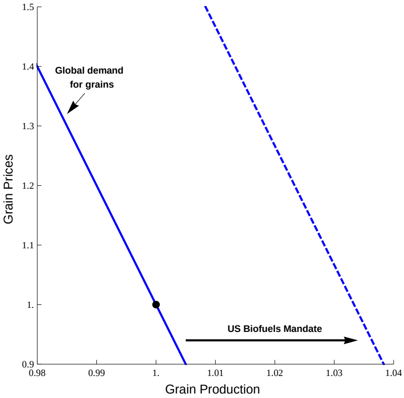
Contributions

- I develop a tractable and flexible empirical dynamic model of land use
  - Estimated with linear regression equation
  - "Euler equation" approach
- Taking dynamics into account implies larger environmental impacts, smaller price impacts from biofuels

Motivation: biofuels policy

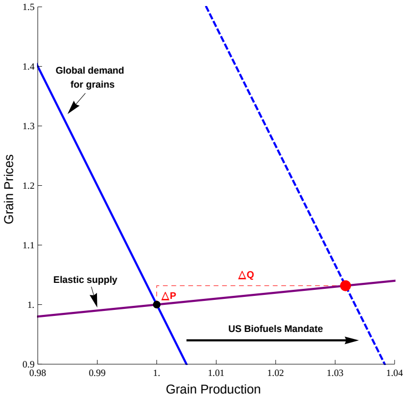
- US biofuels mandate: about 10% of gasoline must come from biofuels (Renewable Fuels Standard)
- Appeal of biofuels: closing the carbon cycle
  - But what is the opportunity cost of the feedstock?
- Biofuels mandate $\Rightarrow$ a long-run increase in demand for grains
  - 35-40% of US corn production used to for ethanol recently
  The RFS Schedule
- Increased demand $\Rightarrow$ higher food prices and/or environmentally destructive land use change

Effects of the US biofuels mandate



price correlations

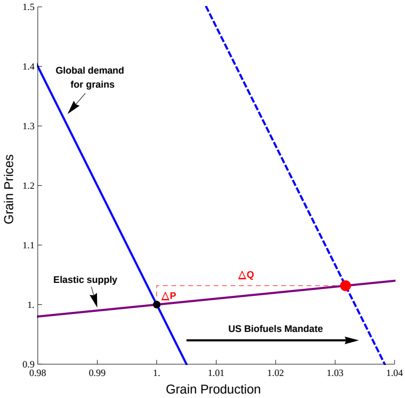
Effects of the US biofuels mandate



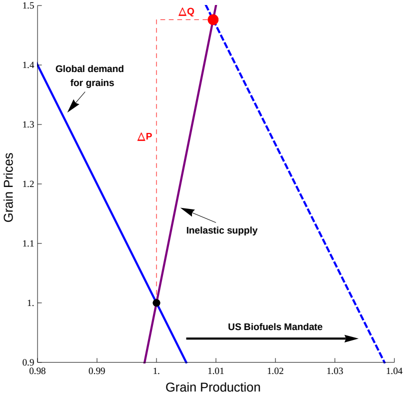
Elastic supply $\Rightarrow$
Environmental Destruction

▸ price correlations

Effects of the US biofuels mandate



Elastic supply ⇒
Environmental Destruction



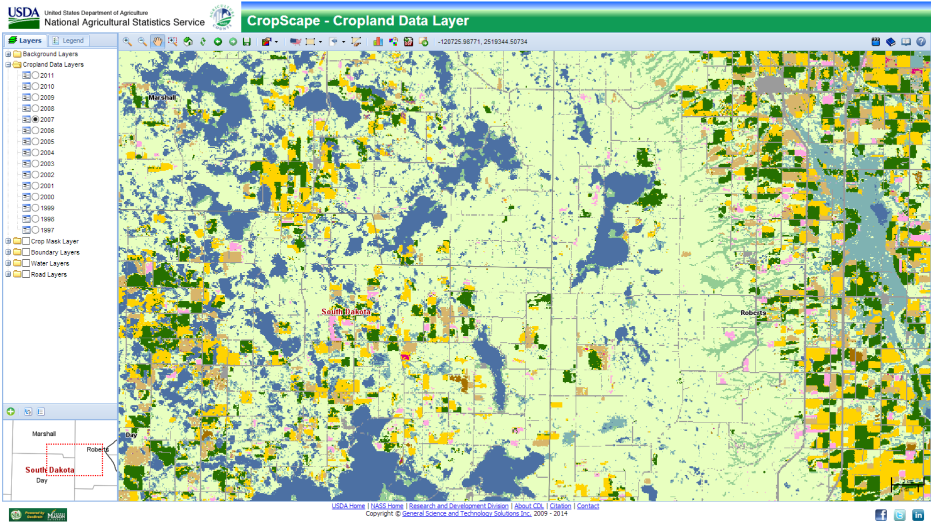
Inelastic supply ⇒
Starvation

price correlations

Corn Prices

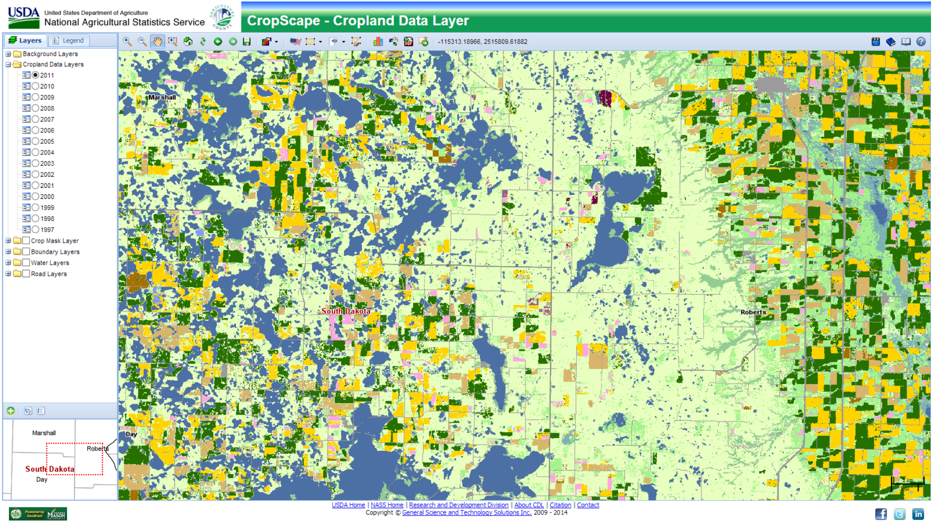
US Dollars per Metric Ton
349.6
321.77
293.94
266.11
238.28
210.45
182.62
154.79
126.97
99.14
71.31
Jun-1998
Jun-1999
Jun-2000
Jun-2001
Jun-2002
Jun-2003
Jun-2004
Jun-2005
Jun-2006
Jun-2007
Jun-2008
Jun-2009
Jun-2010
Jun-2011
Jun-2012
Jun-2013

Choice data preview



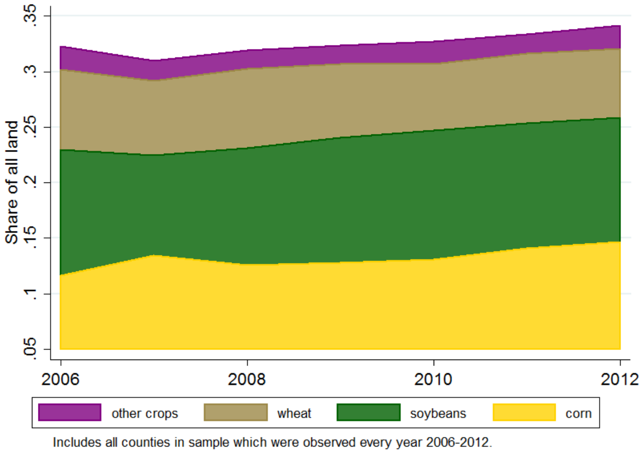
Roberts County, SD, 2007

Choice data preview



Roberts County, SD, 2011

Aggregate acreage



Within land I observe for the entire sample period:

- 32.3% in crops in 2006
- 34.2% in crops in 2012

Intensive vs. extensive margins

- Focus is on the **extensive margin** of agricultural supply, i.e. land use change.
- **Intensive** margin assumed to be small.
- Supporting evidence: working papers by Berry and Schlenker (2011) and Scott (2013).

Empirical work on land use and crop supply

- The most influential papers on biofuels have weak empirical foundations (Searchinger et al., 2008; Tyner et al., 2010)
- Roberts and Schlenker (2013):
  - rare example of study on biofuels based on explicit econometric evidence
  - relies on static anaysis, like most papers on land use change
- Two levels on which dynamic matter:
  1. state dependence
  2. dynamic optimization

Dynamic discrete choice estimation

- Estimate model using linear regression
  - relies on Hotz-Miller (1993) inversion
  - most DDC estimation papers involve non-linear likelihood functions or moment conditions
- "Euler equation" approach
  - have to model field-level dynamics but not market dynamics
  - discrete choice analog of Hall (1978)
    other examples: Altug and Miller (1998), Murphy (2012)
- Unobservable heterogeneity using EM algorithm
  - follows Arcidiacono and Miller (2011)

Outline

1. Model and empirical approach
   - Binary model of crop choice
   - Regression equation construction
   - Extension to unobservable heterogeneity
2. Data and implementation
3. Results
   - Importance of dynamics and unobservable heterogeneity
   - Implications for biofuels policy

Model & Empirical Approach

Binary crop choice model

- A landowner's choice set: $\mathbf{J} = \{crops, other\}$.

- If field i is in state k at time t, then the *expected* profits to land use j are:

$$\pi(j, k, \nu_{it}) = \alpha_{0,j,k} + \alpha_R R_j(\omega_t) + \xi_{jk}(\omega_t) + \nu_{ijt}$$

i: field
j: land use
k: field state
ω: market state (information set for farmers)
R: expected returns, observable to econometrician
ξ: unobservable shock to returns
ν: idiosyncratic field-level shock
α: parameters to be estimated

Assumptions

Assumption 1 (small fields, no externalities)

The distribution of the market state ω_{t+1} conditional on ω_t is not affected by changing the land use in any single field.

Assumption 2 (logit errors)

The idiosyncratic error term ν_{ijt} has a type 1 extreme value distribution, independently and identically distributed across i, j, and t.

Dynamics I

- Landowners maximize expected discounted profits.
- Field states evolve according to a simple deterministic process:

$$k_{i,t+1} = \kappa\left(j_{it}, k_{it}\right) = \begin{cases} 0 & \text{if } j_{it} = \textit{crops} \\ \min\left\{k_{it} + 1, \bar{k}\right\} & \text{if } j_{it} = \textit{other} \end{cases}$$

- No explicit assumptions on the evolution of R and ξ
- Important: estimating the process governing the evolution of the unobservable supply shock ξ is especially difficult

Dynamics II

- β: common discount factor
- Value function:

$$V_t\left(k_{it},\nu_{it}\right)\equiv \max_{\mathbf{j}} E\left[\sum_{s\geq t}^{\infty}\beta^{s-t}\pi\left(\mathbf{j}\left(\omega_s,k_{is},\nu_{is}\right),k_{is},\omega_s,\nu_{is}\right)\middle|k_{it},\omega_t,\nu_{it}\right]$$

where $\mathbf{j}$ represents a policy function.

Assumption 3

Landowners have rational expectations.

Dynamics III

- *ex ante value function*:

$$\bar{V}_t(k) \equiv \int V_t(k,\nu)\, dF(\nu),$$

  the value function integrated over idiosyncratic shocks ν

- *conditional value function*:

$$\delta_t(j,k) \equiv \bar{\pi}_t(j,k) + \beta E_t\left[\bar{V}_{t+1}(\kappa(j,k))\right]$$

  where $\bar{\pi}$ indicates ex ante profits: $\bar{\pi}_t(j,k) = \pi_t(j,k,0)$

- *Conditional choice probabilities* (with logit assumption):

$$p_{jkt} = \frac{\exp(\delta_t(j,k))}{\sum_{j'} \exp(\delta_t(j',k))}$$

Regression equation construction

Steps:

1. Start with condition for indifferent agent
2. Introduce expectational error ("Euler equation" error term)
3. Forward calculation of continuation values using conditional choice probabilities
4. Rearrange into regression equation

Step 1: Indifferent agent condition (Hotz-Miller inversion)

- The Hotz-Miller inversion with logit errors:

$$\ln\left(\frac{p_{jkt}}{p_{j'kt}}\right) = \delta_t\left(j,k\right) - \delta_t\left(j',k\right)$$

- Rewrite as relationship between current profits and continuation values:

$$\bar{\pi}_t\left(j,k\right) - \bar{\pi}_t\left(j',k\right) + \ln\left(\frac{p_{jkt}}{p_{j'kt}}\right) =$$

$$\beta\left(E_t\left[\bar{V}_{t+1}\left(\kappa\left(j,k\right)\right)\right] - E_t\left[\bar{V}_{t+1}\left(\kappa\left(j',k\right)\right)\right]\right)$$

Step 2: Expectational errors

- Expectational error:

$$\varepsilon_t^{CV}(j,k) \equiv \beta\left(E_t\left[\bar{V}_{t+1}(\kappa(j,k))\right] - \bar{V}_{t+1}(\kappa(j,k))\right)$$

- The condition can be rewritten:

$$\bar{\pi}_t(j,k) - \bar{\pi}_t(j',k) + \ln\left(\frac{p_{jkt}}{p_{j'kt}}\right) =$$

$$\beta\left(\bar{V}_{t+1}(\kappa(j,k)) - \bar{V}_{t+1}(\kappa(j',k))\right)$$

$$+\varepsilon_t^{CV}(j,k) - \varepsilon_t^{CV}(j',k)$$

- The expectational error terms are mean uncorrelated with any variables in the information set ω_t.

Step 3: Forward calculation

- Replace the continuation values using the following formula:

$$\bar{V}_t\left(k\right) = -\ln\left(p_{j^*,k,t}\right) + \delta_t\left(j^*, k\right) + \gamma$$

  which holds for **any** land use j^*. This is a special case of Arcidiacono and Miller's (2011) Lemma 1. ▸ derivation

- Recall $\kappa\left(crops, k\right) = 0$ for all k (renewal action)

- By choosing $j^* = crops$, continuation values from $t+2$ onward will cancel:

$$\begin{aligned}
\bar{V}_{t+1}\left(\kappa\left(j,k\right)\right) &= -\ln\left(p_{j^*,\kappa(j,k),t+1}\right) + \bar{\pi}_{t+1}\left(j^*, \kappa\left(j,k\right)\right) + \beta\bar{V}_{t+2}\left(0\right) \\
\bar{V}_{t+1}\left(\kappa\left(j',k\right)\right) &= -\ln\left(p_{j^*,\kappa(j',k),t+1}\right) + \bar{\pi}_{t+1}\left(j^*, \kappa\left(j',k\right)\right) + \beta\bar{V}_{t+2}\left(0\right)
\end{aligned}$$

Step 4: rearrange into regression equation

$$Y_{k,t} = \tilde{\Delta}\alpha_0(k) + \alpha_R \Delta R_t + \tilde{\Delta}\xi_{kt} + \Delta\varepsilon_t^{CV}$$

where

$$\begin{aligned}
Y_{k,t} &= \ln\left(\frac{p_{crops,k,t}}{p_{other,k,t}}\right) + \beta \ln\left(\frac{p_{crops,0,t+1}}{p_{crops,\kappa(other,k),t+1}}\right) \\
\tilde{\Delta}\alpha_0(k) &= \alpha_{0,crops,k} - \alpha_{0,other,k} \\
&\quad + \beta\left(\alpha_{0,crops,0} - \alpha_{0,crops,\kappa(other,k)}\right) \\
\Delta R_t &= R_{crops,t} - R_{other,t} \\
\tilde{\Delta}\xi_t &= \xi_{crops,k,t} - \xi_{other,k,t} + \beta\left(\xi_{crops,0,t+1} + \xi_{crops,\kappa(other,k),t+1}\right) \\
\Delta\varepsilon_t &= \varepsilon_t^{CV}(crops,k) - \varepsilon_t^{CV}(other,k)
\end{aligned}$$

Generalizes to multinomial setting and (almost) any distribution for ν.

Heterogeneity

- z_i: observable persistent field-level characteristic (counties)
- ζ_i: Persistent, unobservable field-level characteristic (binary)
  - estimation idea: EM algorithm (Arcidiacono and Miller, 2011)

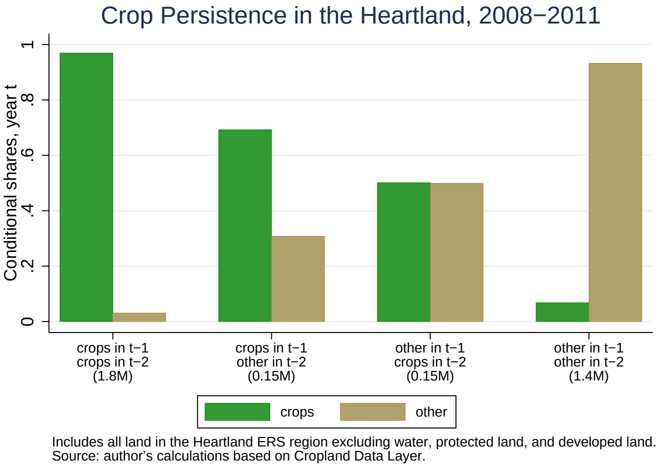
Estimation without unobservable heterogeneity

1. Estimate conditional choice probabilities
2. Construct dependent variable from CCP estimates
3. Linear regression to estimate $\tilde{\Delta}\alpha_{z,\zeta,0}(k)$ and α_R
4. Recover $\alpha_{z,\zeta,0}(j,k)$ from $\tilde{\Delta}\alpha_{z,\zeta,0}(k)$

Estimation with unobservable heterogeneity

1. Estimate conditional choice probabilities **for each unobservable type using EM algorithm**
2. Construct dependent variable from CCP estimates
3. Linear regression to estimate $\tilde{\Delta}\alpha_{z,\zeta,0}(k)$ and α_R
4. Recover $\alpha_{z,\zeta,0}(j,k)$ from $\tilde{\Delta}\alpha_{z,\zeta,0}(k)$

Identification of unobservable heterogeneity



Formal identification papers: Hall and Zhou (2003), Kasahara and Shimotsu (2009) ▸ EM details

Data & Measurement

Data & measurement overview

- Field-level panel where field $\equiv$ spatial point
- "Crops": all crop classifications except hay
- "Other": pasture, hay, grassland, forests, other forms of non-managed land
- Developed land, protected areas, and water excluded from the sample ▸ Classification table

Crop Returns

- Returns to cropland is a weighted average across crops:

$$R_{crops,t,z} = \frac{\sum_{c \in \mathbf{C}} A_{cts} R_{ctz}}{\sum_{c \in \mathbf{C}} A_{cts}}$$

  where A_{cts} is the harvested area for US state s.

- $\mathbf{C}$ ={corn, soybeans, winter wheat, durum wheat, other wheat, barley, oats, rice, upland cotton, pima cotton}

- Expected returns $R_{c,t,z}$ measure the expected returns during *planting season*:

$$R_{ctz} = (P_{ctz} - e_{ctz}) \cdot YIELD_{ctz}$$

Expected yields

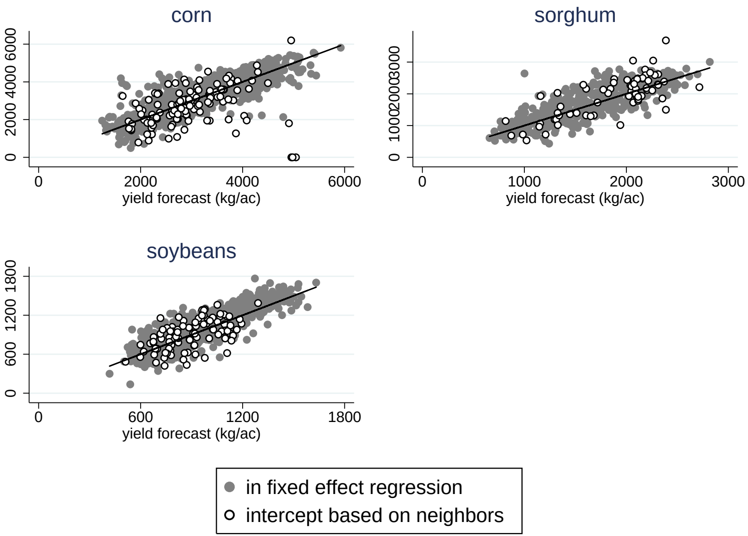
- Yields based on weather data, county fixed effects, and a linear time trend:

$$\ln\left(YIELD_{ctz}\right) = \theta_{cz} + \theta_{cw} W_{tz} + \theta_{ct} t + \varepsilon_{ctz}$$

- For county-crops with insufficient data, I impute fixed effects based on a weighted average of fixed effects for nearby counties.

- Weather data and specification from Schlenker and Roberts (PNAS, 2009).

Yield forecasts



Small grains

Cotton

Identification: fixed effects

Think of the data as a panel in n and t, where n indexes a county, field type, and field state ($n = (z, \zeta, k)$)

$$Y_{nt} = \tilde{\Delta}\alpha_{0n} + \alpha_{R\zeta} R_{nt} + \tilde{\Delta}\xi_{nt} + \Delta\varepsilon_{nt}^{V}$$

The rational expectations assumption implies the moment

$$\forall t : \ E\left[\Delta\varepsilon_{nt}^{V} R_{nt}\right] = 0.$$

However, fixed effects estimation requires a stronger assumption:

$$\forall t, t' : \ E\left[\Delta\varepsilon_{nt}^{V} R_{nt'}\right] = 0,$$

which is not implied by the model and unlikely to be true.

Identification: first differences

$$\begin{aligned} Y_{n,t+1} - Y_{nt} = \quad & \alpha_{R\zeta}\left(R_{n,t+1} - R_{nt}\right) \\ & + \tilde{\Delta}\xi_{n,t+1} - \tilde{\Delta}\xi_{n,t} \\ & + \tilde{\Delta}\varepsilon^{V}_{n,t+1} - \tilde{\Delta}\varepsilon^{V}_{nt} \end{aligned}$$

I use the following moments for estimation:

$$E\left[\begin{pmatrix} 1 \\ R_{nt} \\ CYIELD_{nt} \end{pmatrix}\left(\tilde{\Delta}\xi_{n,t+1} - \tilde{\Delta}\xi_{n,t}\right)\right] = 0$$

where $CYIELD_{nt}$ is expected caloric yield.

Results

Long-run elasticities

- Long-run acreage-price elasticity:

$$\left(\sum_{z}\sum_{\zeta}A^{*}_{z\zeta}\left(R_{zt}\right)\right)^{-1}\left(\sum_{z}\sum_{\zeta}\left(A^{*}_{z\zeta}\left(R_{zt'}\right)-A^{*}_{z\zeta}\left(R_{zt}\right)\right)\frac{P_{zt}}{P_{zt'}-P_{zt}}\right)$$

  - $A^{*}\left(R\right)$: is the steady-state acreage implied by the dynamic model with returns fixed at R
  - P_{zt}: price index
  - $t=2012$, t' is a hypothetical period with 10% higher output prices
- Long-run calorie-price elasticity defined similarly

Long-run elasticity estimates I

	No Unobs. Heterogeneity		Two Types Per County	
	Acreage	Calorie	Acreage	Calorie
Static model ($\bar{k} = 0$)	-0.0012	-0.0013	0.0600	0.0624
	(0.0358)	(0.0359)	(0.0460)	(0.0471)
Myopic models ($\beta = 0$)				
$\bar{k} = 1$	0.0703	0.0693	0.0037	0.0054
	(0.1427)	(0.1416)	(0.0380)	(0.0388)
$\bar{k} = 2$	0.0171	0.0160	-0.0067	-0.0063
	(0.1839)	(0.1820)	(0.0507)	(0.0500)
Dynamic models ($\beta = .9$)				
$\bar{k} = 1$	0.6669	0.6144	0.5449	0.5990
	(0.5470)	(0.5031)	(0.1764)	(0.1944)
$\bar{k} = 2$	0.4757	0.4519	0.4152	0.4425
	(0.5151)	(0.4932)	(0.1610)	(0.1724)

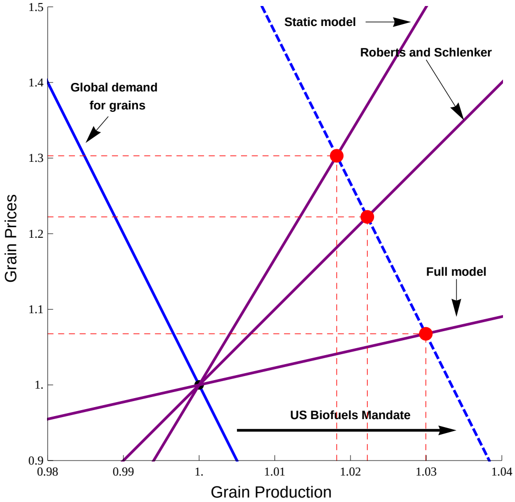
▸ Full dynamic parameter estimates ▸ Posteriors vs. slope index ▸ Different measures of returns

Long-run elasticity estimates II

CCPs	Weighted	Regression Approach FE	FD	FDIV
smoothed	no	0.2909	0.2840	0.2540
		(0.0246)	(0.0211)	(0.0301)
		(0.2376)	*(0.1976)*	*(0.2506)*
smoothed	yes	0.4485	0.3803	0.4325
		(0.0236)	(0.0203)	(0.0278)
		(0.2021)	*(0.1632)*	*(0.2068)*
truncated	no	0.3657	0.3674	0.3068
		(0.0374)	(0.0318)	(0.0439)
		(0.1972)	*(0.1650)*	*(0.2253)*
truncated	yes	0.4136	0.3860	0.4152
		(0.0242)	(0.0211)	(0.0302)
		(0.1519)	*(0.1185)*	*(0.1610)*

Regression approaches are fixed effects, first differences, and first differences with instruments. All models feature two unobservable types, two periods of state dependence, and $\beta = .9$. Standard errors in parentheses standard errors with autocorrelation in italics.

Effects of the US biofuels mandate



Relative to Roberts and Schlenker (forthcoming *AER*), my supply elasticity estimate predicts a 35% larger land use increase and 70% smaller price increase in the long run.

Are these elasticities unrealistically high? (No!)

Another simulation:

1. Initialize acreage levels to steady state distributions with returns fixed at 2006 levels
2. Simulate deterministic process: historical returns are attained for 2007-2011, and then prices are held constant at 6.8% higher than 2006 levels forever after
3. Agents have perfect foresight

Simulation results: land in crops in 2012 is 6.1% higher than in 2006.

From 2006 to 2012, land in crops actually increased by 5.7%
(within states which have been in the Cropland Data Layer since 2006)

Thank you!

Step 3: Forward calculation

By integrating the conditionally independent logit errors, we can derive simple expressions for conditional choice probabilities and the ex ante value function:

$$p_{jkt} = \frac{\exp(\delta_t(j,k))}{\sum_{j'} \exp(\delta_t(j',k))} \tag{1}$$

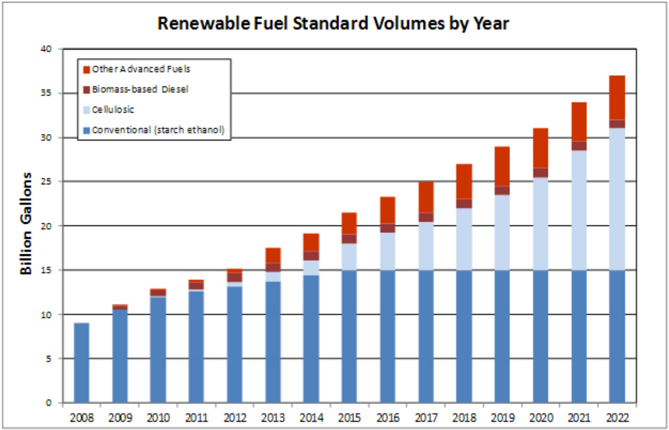
$$\bar{V}_t(k) = \ln\left(\sum_{j'} \exp\left(\delta_t(j',k)\right)\right) + \gamma. \tag{2}$$

Adding and subtracting $\delta_t(j,k)$ in equation (1), and substituting using equation (2):

$$\bar{V}_t(k) = -\ln(p_{jkt}) + \delta_t(j,k) + \gamma,$$

where γ is Euler's gamma. back

Renewable fuel standards



Source: US Department of Energy

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Unobservable heterogeneity: formalities

- **CCP's contingent on unobservable characteristics**:

$$p_{z\zeta t}\left(j,k\right)$$

- **Prior probabilities of unobservable** ζ, conditional on z and k:

$$\mu_{z\zeta}\left(k\right) \equiv Pr\left(\zeta_i = \zeta \middle| k_{i1}, i \in I_z\right)$$

where I_z denotes the set of fields with observable type z.

- Define **posterior probabilities**:

$$q_{i\zeta} \equiv Pr\left(\zeta_i = \zeta \middle| \mathbf{j}_i, \mathbf{k}_i\right) = \mu_{z(i)\zeta}\left(k\right) \prod_{t=1}^{T} p_{z(i)\zeta t}\left(j_{it}, k_{it}\right)$$

- where $z\left(i\right)$ is the observable type of field i.

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EM Algorithm

$$\text{M step:} \quad \hat{p}^{(freq,m)}_{z\zeta t}(j,k) = \frac{\sum_{i\in I_z} q^{(m-1)}_{i\zeta}\mathbf{1}[j_{it}=j, k_{it}=k]}{\sum_{i\in I_z} q^{(m-1)}_{i\zeta}\mathbf{1}[k_{it}=j]}$$

$$\hat{p}^{(m)}_{z\zeta t}(j,k) = \frac{\sum_{z'\in Z_s} w_{zz'}\hat{p}^{(freq,m)}_{z'\zeta t}(crops,k)}{\sum_{z'\in Z_s} w_{zz'}}$$

$$\hat{\mu}^{(m)}_{z\zeta}(k) = \frac{\sum_{i\in I_z} q^{(m-1)}_{i\zeta}\mathbf{1}[k_{i1}=k]}{\sum_{i\in I_z} q^{(m-1)}_{i\zeta}}$$

$$\text{E step:} \quad q^{(m)}_{i\zeta} = \hat{\mu}^{(m)}_{z\zeta}(k_{i1})\prod_{t=1}^{T}\hat{p}^{(m)}_{z\zeta t}(j_{it},k_{it})$$

- m denotes values at the mth iteration
- Z_s: set of counties in US state s
- Iterate E and M steps until convergence
  - no monotonicity (and not ML) because of smoothing
  - method of moments estimator, EM algorithm finds solution

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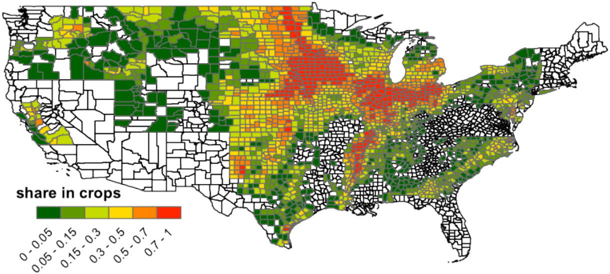
Dynamic estimates: details

State dependence $\bar{k}$	1	1		2	2	
Field types	1	2		1	2	
Type		High	Low		High	Low
α_R	0.1405	0.0359	0.3822	0.0553	-0.0041	0.2333
	(0.0632)	(0.0595)	(0.0740)	(0.0593)	(0.0706)	(0.0788)
Average intercepts (α_0)						
$k = 0$	-0.3268	1.1118	-2.6980	-0.0546	0.9259	-2.1024
	(0.1677)	(0.1579)	(0.1962)	(0.1632)	(0.1944)	(0.2170)
$k = 1$	-4.8413	-0.1744	-5.2899	-2.3996	-1.3241	-1.7699
	(0.1677)	(0.1579)	(0.1962)	(0.1632)	(0.1944)	(0.2170)
$k = 2$	–	–	–	-5.7812	-1.7508	-5.0839
	–	–	–	(0.1632)	(0.1944)	(0.2170)
Type's share of fields	1.0000	0.2702	0.7298	1.0000	0.2571	0.7429
Share in crops	0.2496	0.8624	0.0226	0.2516	0.8772	0.0350
Long run acreage-price elasticity	1.1353	0.4232		0.4757	0.4152	
	(0.4714)	(0.1160)		(0.5151)	(0.1610)	
Long run calorie-price elasticity	1.0379	0.4525		0.4519	0.4425	
	(0.4261)	(0.1270)		(0.4932)	(0.1724)	
Counties	1978	1978		1978	1978	
County-years	8281	8281		6303	6303	

CCP truncation used in the first stage, firt differences with instruments used in the second, $\beta = .9$. R measured in $100/acre. Standard errors in parentheses. back

Map of sample counties



Counties in my sample account account for 91% of US cropland.

On average, counties have ≈2900 fields.

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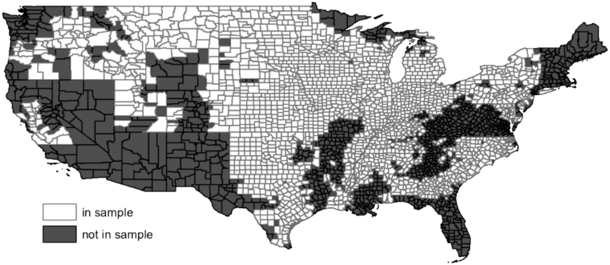
Black and white version

Map of sample counties



Counties in my sample account account for 91% of US cropland.

On average, counties have ≈2900 fields.

▸ back

Land use classifications

Land Cover Classifications

CDL Classification	Mine	land cover %	CDL Classification	Mine	land cover %
Grassland/Herbaceous	other	18.03	Barley	crops	0.14
Shrub/Scrub	other	11.98	Sunflower	crops	0.11
Deciduous Forest	other	11.81	Dry Beans	crops	0.1
Evergreen Forest	other	8.31	Sugarbeets	crops	0.09
Corn	crops	8.04	Oats	crops	0.09
Soybeans	crops	6.26	Durum Wheat	crops	0.09
Pasture/Hay	other	5.24	Canola	crops	0.09
Developed, Open Space	excluded	3.83	Peanuts	crops	0.08
Woody Wetlands	other	3.6	Potatoes	crops	0.07
Winter Wheat	crops	3.05	Sod/Grass Seed	other	0.06
Pasture/Grass	other	2.82	Almonds	crops	0.05
Fallow/Idle Cropland	other	2.04	Peas	crops	0.04
Open Water	excluded	1.77	Grapes	crops	0.04
Non-alfalfa Hay	other	1.67	Millet	crops	0.04
Developed, Low Intensity	excluded	1.53	Rye	crops	0.04
Alfalfa	other	1.33	Lentils	crops	0.03
Cotton	crops	1.31	Walnuts	crops	0.03
Herbaceous Wetlands	other	1.29	Apples	crops	0.03
Spring Wheat	crops	1.18	Pecans	crops	0.02
Mixed Forest	other	0.78	Dbl. Crop WinWht/Sorghum	crops	0.02
Barren Land	other	0.74	Dbl. Crop WinWht/Cotton	crops	0.02
Developed, Medium Intensity	excluded	0.56	Sweet Corn	crops	0.02
Sorghum	crops	0.44	Aquaculture	excluded	0.02
Dbl. Crop WinWht/Soy	crops	0.41	Sugarcane	crops	0.02
Rice	crops	0.24	Clover/Wildflowers	other	0.02
Developed, High Intensity	excluded	0.2			

Percentages are for counties in my sample in 2011. Only land cover classifications with at least 1000 sample observations are listed above.

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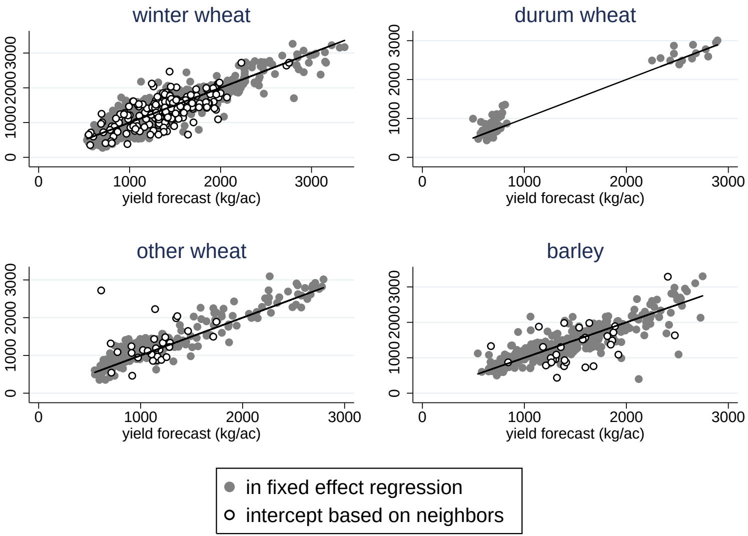
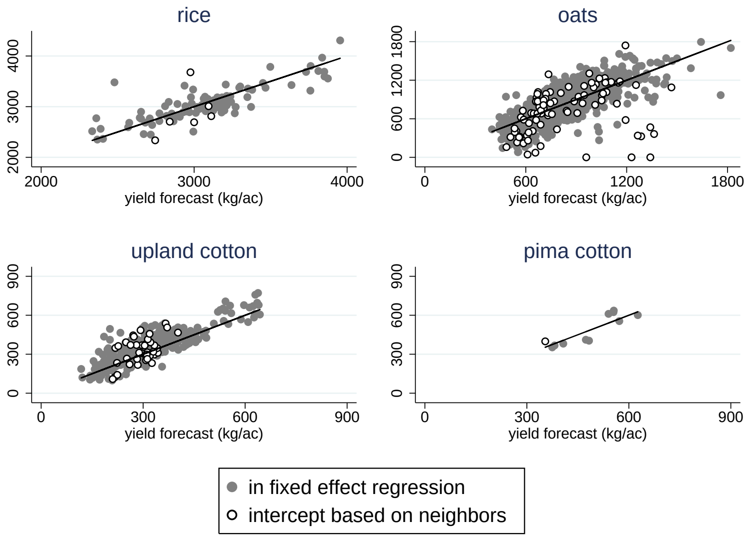
Yield forecasts



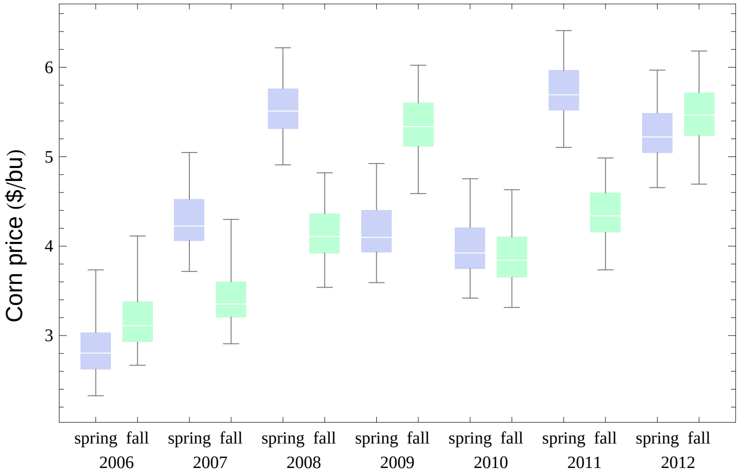
▸ Corn, soybeans ▸ Cotton

Yield forecasts



Corn, soybeans   Small grains

Corn Prices



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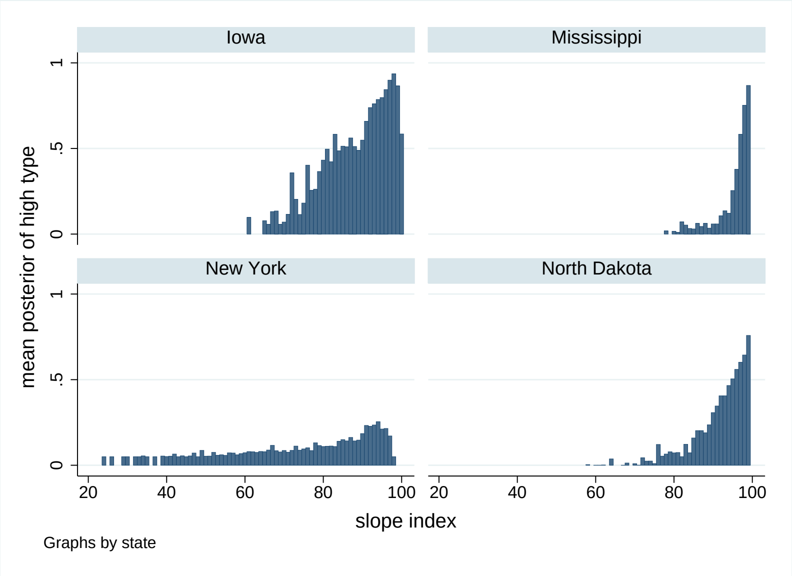
Posteriors



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Elasticity estimates with different models of returns

Acreage elasticity	0.4152	0.4668	0.3224	0.3026
	(0.1610)	(0.1642)	(0.1664)	(0.1579)
Caloric Elasticity	0.4425	0.4983	0.3420	0.3205
	(0.1724)	(0.1759)	(0.1757)	(0.1669)
Price forecasts use	Planting season futures		Futures from prev. fall	
Costs per acre	Proportional to yields	Flat within region	Proporitional to yields	Flat within region

Long-run elasticities for models with two unobservable types and two periods of state dependence. CCP truncation was used in the first stage, first differences with instruments were used in the second, and $\beta = .9$. Standard errors in parentheses.

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Feb-March CBOT Futures Price Correlations, 1997-2011

	corn	soybeans	wheat	oats
corn	1.0000			
soybeans	0.9787	1.0000		
wheat	0.9600	0.9687	1.0000	
oats	0.9750	0.9752	0.9812	1.0000

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