Dynamic Discrete Choice Estimation of Agricultural Land Use

Paul T. Scott

New York University

ptscott@gmail.com

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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?
  - Relevant for many agricultural and environmental policy questions

Contributions

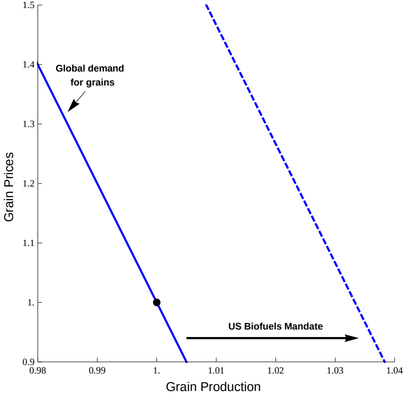
- I develop a tractable and flexible empirical dynamic model of land use
- Taking dynamics into account implies larger environmental impacts, smaller price impacts from biofuels

Motivation: biofuels policy

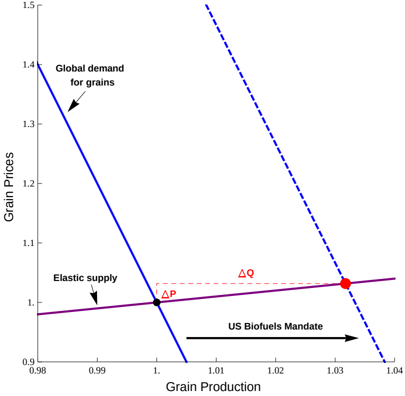
- US biofuels mandate: about 10% of gasoline must come from biofuels (Renewable Fuels Standard)
- Appeal of biofuels: closing the carbon cycle
  - But what is the opportunity cost of the feedstock?
- Biofuels mandate $\Rightarrow$ a long-run increase in demand for grains
  - 35-40% of US corn production 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



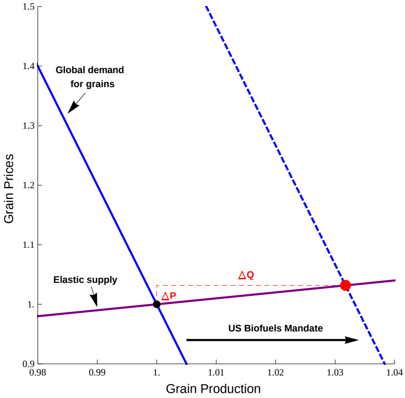
Effects of the US biofuels mandate

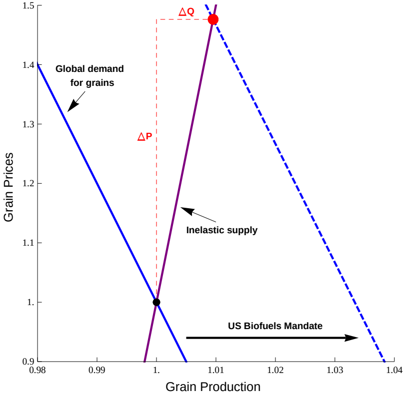


Elastic supply $\Rightarrow$

Environmental Destruction

Effects of the US biofuels mandate





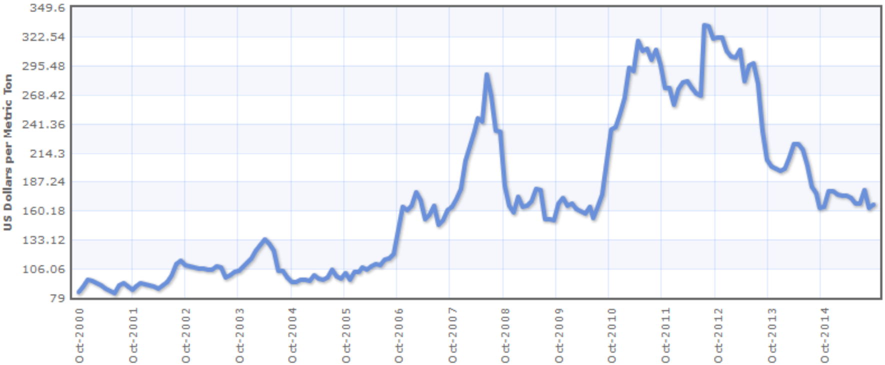
Elastic supply $\Rightarrow$
Environmental Destruction

Inelastic supply $\Rightarrow$
Starvation

ILUC assessments

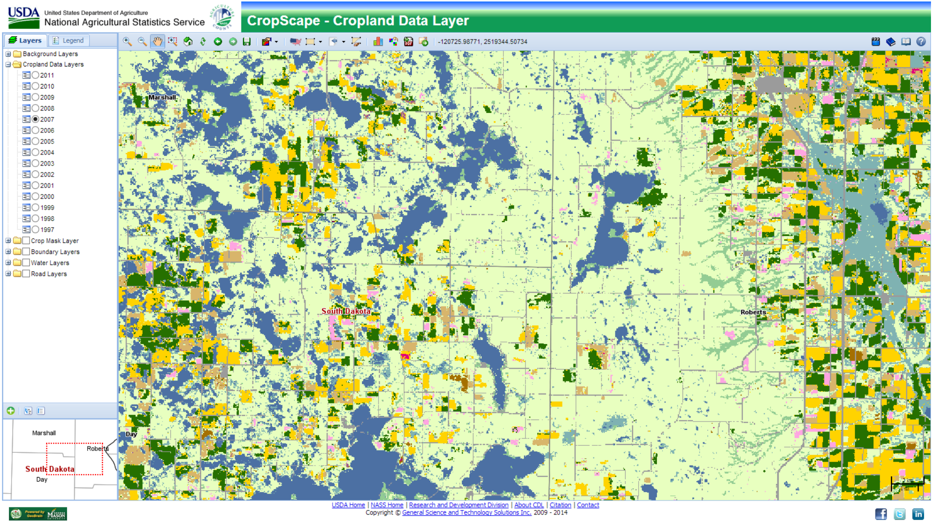
Source: California Air Resources Board

Corn Prices



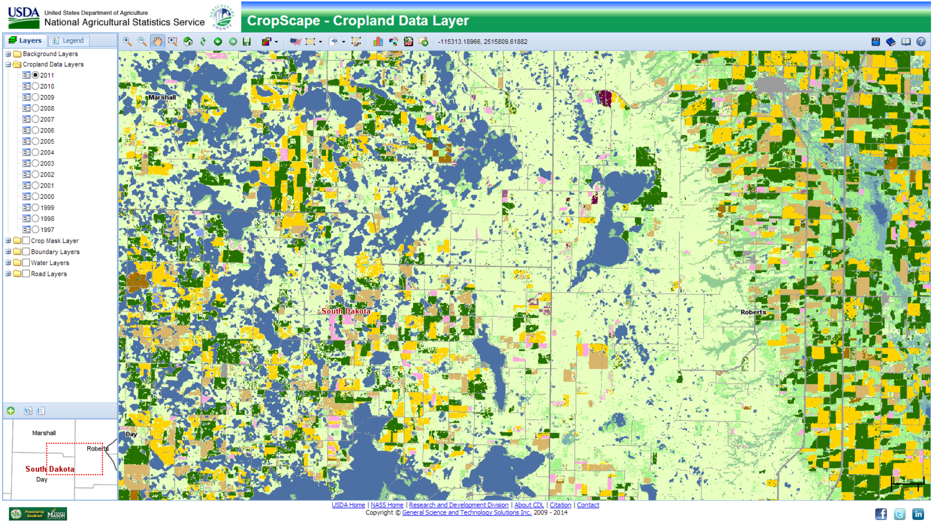
▸ price correlations

Choice data preview



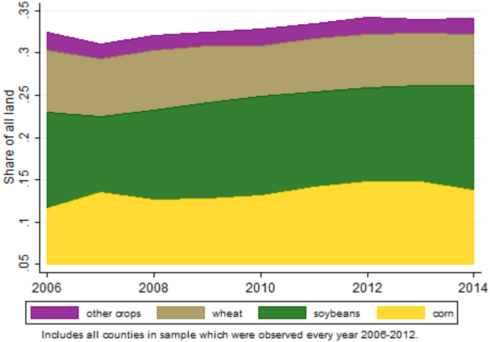
Roberts County, SD, 2007

Choice data preview



Roberts County, SD, 2011

Aggregate acreage



Within land I observe for the entire sample period:

- 32.4% in crops in 2006
- 34.1% in crops in 2014

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: Berry and Schlenker (2011), Scott (2013), Sant'Anna (2015).

Agricultural Supply Estimation

- Common in empirical agricultural economics are models featuring state dependence: Nerlove (1956), Lubowski (2002)
  - distinction between short- and long-run comes from changes compounding over time, behavior in current period is function of current price and current state
- My estimation strategy differs in allowing for dynamically optimizing agents
  - landowners may respond differently to different types of price variation
  - important if we want to predict response to counterfactual price variation that is (potentially) different than the type of price variation in the data
- Relative to adaptive expectations models,
  - My model is computationally simpler to estimate
  - My framework does not require the econometrician to specify the full state space and determine how all state variables evolve

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
  - allows for unobservable market-level shocks
  - 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:

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

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: Field-Level

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

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

- 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: Alternative

- Alternative field-level dynamics:

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

- With the original κ^{+}, $j_{it} = \mathit{crops}$ is a renewal action here, $(j_{it}, j_{i,t+1}) = (\mathit{crops}, \mathit{other})$ is a renewal sequence

Dynamics: Value Function

- β: common discount factor
- Value function:

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

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

Assumption 3

Landowners have rational expectations.

Dynamics: Definitions

- *ex ante value function*:

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

the value function integrated over idiosyncratic shocks ν

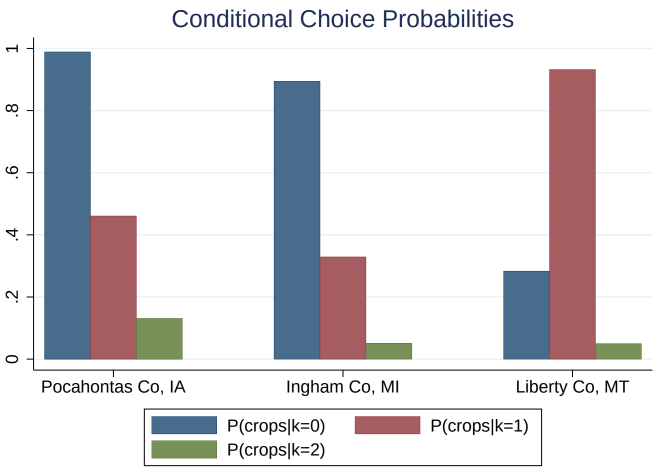
- *conditional value function*:

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

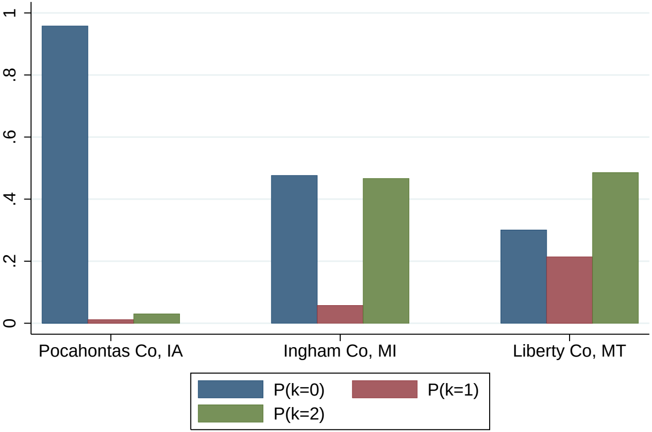
where $\bar{\pi}$ indicates ex ante profits: $\bar{\pi}_t(j,k) = \pi_t(j,k,0)$

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

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


Conditional Choice Probabilities
0
.2
.4
.6
.8
1
Pocahontas Co, IA
Ingham Co, MI
Liberty Co, MT
P(crops|k=0)
P(crops|k=1)
P(crops|k=2)

Field State Shares



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:

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

- 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:

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

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

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

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

$$\bar{V}_{t+1}(\kappa(j,k)) = -\ln\left(p_{j^*,\kappa(j,k),t+1}\right) + \bar{\pi}_{t+1}\left(j^*, \kappa(j,k)\right) + \beta\bar{V}_{t+2}(0)$$

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

Step 4: rearrange into regression equation

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

where

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

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

Generality

We can construct regressions like this pretty generally. The necessary ingredients for the "ECCP approach" (Euler equations in conditional choice probabilities):

- State variables can be decomposed into market-level and agent-specific. In other words, no dynamic games.
- Finite dependence (Arcidiacono and Miller, 2011) in the agent-specific states: basically, the idea that when a state variable is perturbed, it can be returned to another path within a finite amount of time.
- Kalouptsidi, Scott, Souza-Rodrigues (2020) offers several examples and supporting results.

Other Applications

- De Groote and Verboven (2019): solar panel installation
- Sharon Traiberman (2019): occupational choice
- Diamond, McQuade, Qian (2019): neighborhood choice
- Almagro and Dominguez-Iino (2021): neighborhood choice
- Jared Hutchins (2020): dairy cow culling
- Araujo, Costa, Sant'Anna (2021): deforestation, Brazil
- Hsiao (2021): deforestation, Indonesia and Malaysia

Identification of payoff parameters

- The regression idenifies one value of

$$\begin{aligned}\tilde{\Delta}\alpha_0(k) &= \alpha_{0,crops,k} - \alpha_{0,other,k} \\ &\quad + \beta\left(\alpha_{0,crops,0} - \alpha_{0,crops,\kappa(other,k)}\right)\end{aligned}$$

  for each k

- However, we have $2k$ values of α_0 in the profit function for each k: $\alpha_{0,crops,k}$ and $\alpha_{0,other,k}$
- For identification, I assume that $\alpha_{0,other,k} = 0$ for all k

Identification of counterfactuals

- For identification, I assume that $\alpha_{0,other,k} = 0$
- Such restrictions are often called "normalizations" in the literature, but they are substantive restrictions in priciple (Magnac and Thesmar, 2002). Note that a normalization (in the traditional sense) would only allow us to fix $\alpha_{0,other,k} = 0$ for *one single k*
- However, more recent work (Norets and Tang, 2014; Kalouptsidi, Scott, and Souza-Rodrigues, 2021) has considered whether these restrictions actually matter for counterfactuals
    - Turns out counterfactuals in this paper (i.e., long run elasticity calculations) are identified, meaning that the above restriction is harmless

Identification of counterfactuals

- Many counterfactuals that shift payoffs are identified (in the sense that the under-identification of DDC payoffs doesn't matter).
- If is very "unlikely" that counterfactuals that affect the transition process will be identified.
- A correlary is that counterfactuals in dynamic discrete games are "unlikely" to be identified. (See Kalouptsidi, Scott, and Souza-Rodrigues, 2016).

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

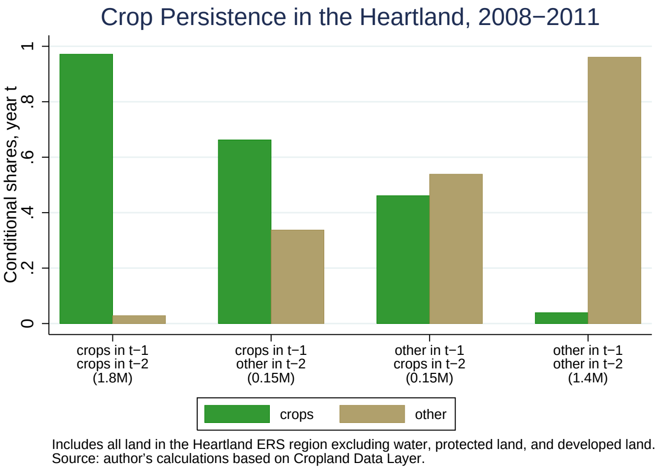
1. Estimate conditional choice probabilities
2. Construct dependent variable from CCP estimates
3. Linear regression to estimate $\tilde{\Delta}\alpha_{z,\zeta,0}(k)$ and α_R
4. Recover $\alpha_{z,\zeta,0}(j,k)$ from $\tilde{\Delta}\alpha_{z,\zeta,0}(k)$

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 $\tilde{\Delta}\alpha_{z,\zeta,0}(k)$

Note: the first-stage here is super non-parametric and that's not necessarily a good thing. E.g., I'm not imposing that first-stage CCP estimates could actually come from a dynamic model. I'll mention approaches based on Ackerberg (2009) if Gautam hasn't already.

Identification of unobservable heterogeneity



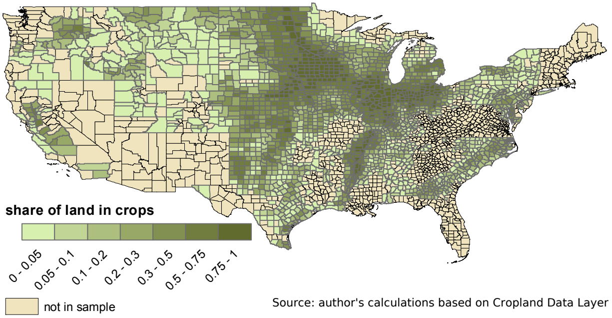
Formal identification papers: Hall and Zhou (2003), Kasahara and Shimotsu (2009) ▸ EM details

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

Map of sample counties



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

On average, counties have ≈2900 fields.

back

Black and white version

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

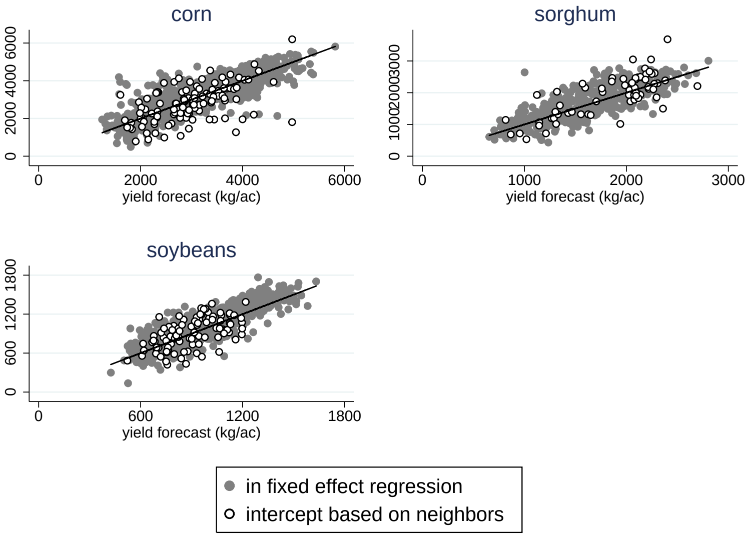
- Yields based on weather data, county fixed effects, and a linear time trend:

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

- 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 ($n = (z, \zeta, k)$)

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

The rational expectations assumption implies the moment

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

However, fixed effects estimation requires a stronger assumption:

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

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:

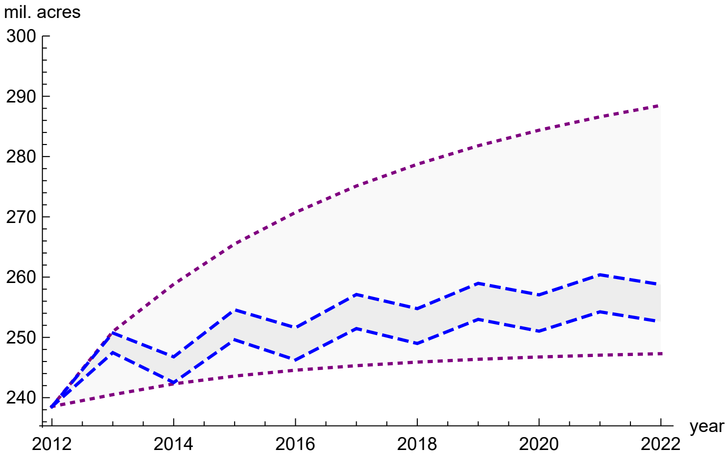
$$\left(\sum_{z}\sum_{\zeta}A^{*}_{z\zeta}\left(R_{zt}\right)\right)^{-1}\left(\sum_{z}\sum_{\zeta}\left(A^{*}_{z\zeta}\left(R_{zt'}\right)-A^{*}_{z\zeta}\left(R_{zt}\right)\right)\frac{P_{zt}}{P_{zt'}-P_{zt}}\right)$$

  - $A^{*}\left(R\right)$: is the steady-state acreage implied by the dynamic model with returns fixed at R
  - P_{zt}: price index
  - $t = 2006$, t' is a hypothetical period with 100% higher output prices
- Long-run calorie-price elasticity defined similarly

	Two Types Per County	
	Acreage	Calorie
Static model ($\bar{k} = 0$)	0.1008	0.1025
	(0.0121)	(0.0125)
Myopic models ($\beta = 0$)		
$\bar{k} = 1$	0.0672	0.0667
	(0.0061)	(0.0061)
$\bar{k} = 2$	0.0456	0.0446
	(0.0088)	(0.0088)
$\bar{k} = 2$ (alternative κ^+)	0.0994	0.1005
	(0.0137)	(0.0140)
Dynamic models ($\beta = .9$)		
$\bar{k} = 1$	0.3191	0.3088
	(0.0721)	(0.0680)
$\bar{k} = 2$	0.4584	0.4694
	(0.0418)	(0.0418)
$\bar{k} = 2$ (alternative κ^+)	0.3501	0.3680
	(0.0203)	(0.0217)

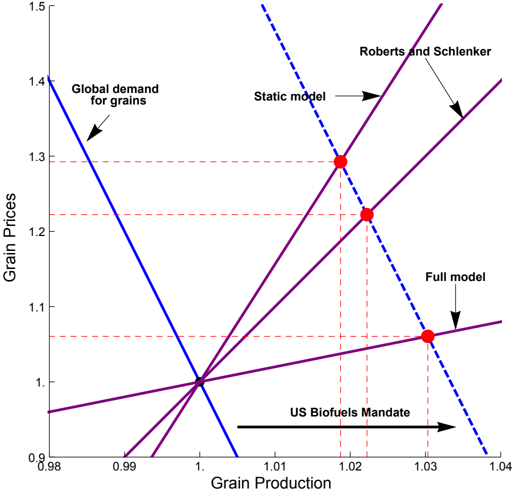
Posteriors vs. slope index

Stability of acreage levels



Forward simulated acreage with returns fixed at 2006 levels indefinitely. Dashed lines are 90% confidence interval for total acreage levels in model with unobservable heterogeneity. Dotted line are 90% confidence interval for model without unobservable heterogeneity. Initial distribution of field states in 2012 set equal to the average distribution of field states by county and unobservable type in the sample. Both models are renewal action models with $\bar{k} = 2$, $\beta = .9$, and were estimated using first differences with instruments.

Effects of the US biofuels mandate



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)

Are these elasticities unrealistically high? (Maybe, if you interpret them incorrectly)

- An important difference from Roberts and Schlenker: cost variation
- Roberts and Schlenker estimate a supply elasticity (with respect to output prices) directly without controlling for variation in costs
- Their elasticity therefore corresponds to a compound derivative:

$$\left(\frac{\partial Q}{\partial P} + \frac{\partial Q}{\partial C}\frac{dC}{dP}\right)\frac{P}{Q}$$

- My elasticity is a partial derivative:

$$\frac{\partial Q}{\partial P}\frac{P}{Q}$$

Conclusion

- ECCP approach, suitable to modeling land use change and other things
  - Fully dynamic model estimated with regression equation
  - Euler equation approach avoids needs for full model of state variables; data limitations show up in an error term (like static applied micro models) rather than necessarily leading to model misspecification
- Dynamic models with heterogeneity generate quite stable simulations
- Estimated dynamic models have larger long-run land use elasticities, higher environmental impacts from biofuels production

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:

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

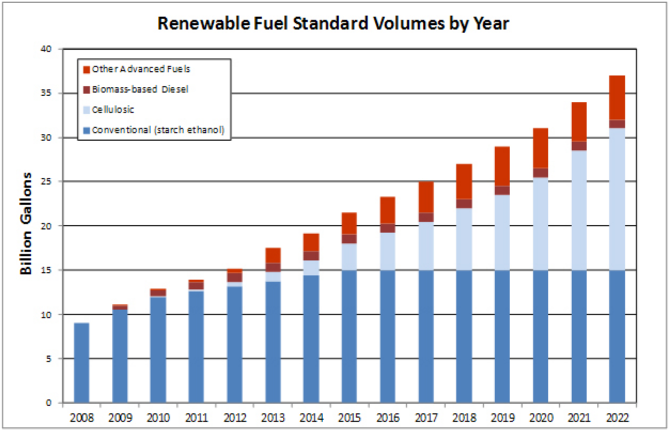
$$\bar{V}_t(k) = \ln\left(\sum_{j'} \exp\left(\delta_t\left(j', k\right)\right)\right) + \gamma. \tag{2}$$

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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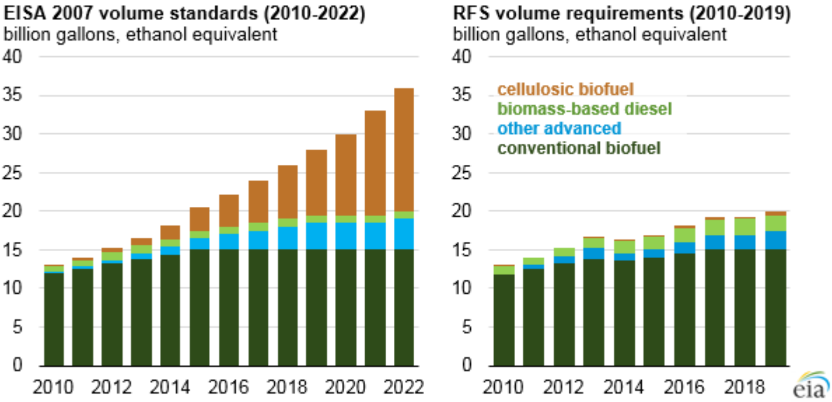
Renewable fuel standards



Source: US Energy Information Administration

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Unobservable heterogeneity: formalities

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

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

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

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

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

- Define **posterior probabilities**:

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

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

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EM Algorithm

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

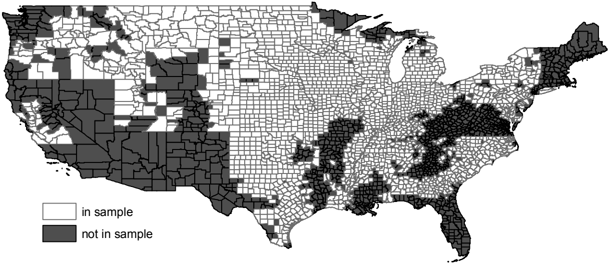
$$\hat{p}^{(m)}_{z\zeta t}(j,k) = \frac{\sum_{z'\in Z_s} w_{zz'}\hat{p}^{(freq,m)}_{z'\zeta t}(crops,k)}{\sum_{z'\in Z_s} w_{zz'}}$$

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

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

- 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

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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Land use classifications

Land Cover Classifications

CDL Classification	My Classification	land cover %		CDL Classification	My C
Grassland/Herbaceous	other	18.26	Developed, High Intensity	excluded	0.20
Deciduous Forest	other	11.88	Barley	crops	0.14
Shrub/Scrub	other	11.45	Sunflower	crops	0.11
Corn	crops	8.23	Dry Beans	crops	0.10
Evergreen Forest	other	8.01	Sugarbeets	crops	0.09
Soybeans	crops	6.42	Durum Wheat	crops	0.09
Pasture/Hay	other	5.30	Oats	crops	0.09
Developed, Open Space	excluded	3.84	Canola	crops	0.09
Woody Wetlands	other	3.58	Peanuts	crops	0.08
Winter Wheat	crops	3.11	Potatoes	crops	0.07
Pasture/Grass	other	2.85	Sod/Grass Seed	other	0.06
Fallow/Idle Cropland	other	2.07	Almonds	crops	0.05
Open Water	excluded	1.76	Peas	crops	0.04
Non-alfalfa Hay	other	1.69	Millet	crops	0.04
Developed, Low Intensity	excluded	1.52	Grapes	crops	0.04
Alfalfa	other	1.35	Rye	crops	0.04
Cotton	crops	1.32	Lentils	crops	0.03
Herbaceous Wetlands	other	1.30	Apples	crops	0.03
Spring Wheat	crops	1.21	Walnuts	crops	0.03
Mixed Forest	other	0.74	Dbl. Crop WinWht/Sorghum	crops	0.02
Barren Land	other	0.69	Pecans	crops	0.02
Developed, Medium Intensity	excluded	0.54	Dbl. Crop WinWht/Cotton	crops	0.02
Sorghum	crops	0.44	Sweet Corn	crops	0.02
Dbl. Crop WinWht/Soy	crops	0.42	Aquaculture	excluded	0.02
Rice	crops	0.24	Clover/Wildflowers	other	0.02

Percentages are for counties in my sample in 2011. Only land cover classifications with at least 950 sample observations are listed above.

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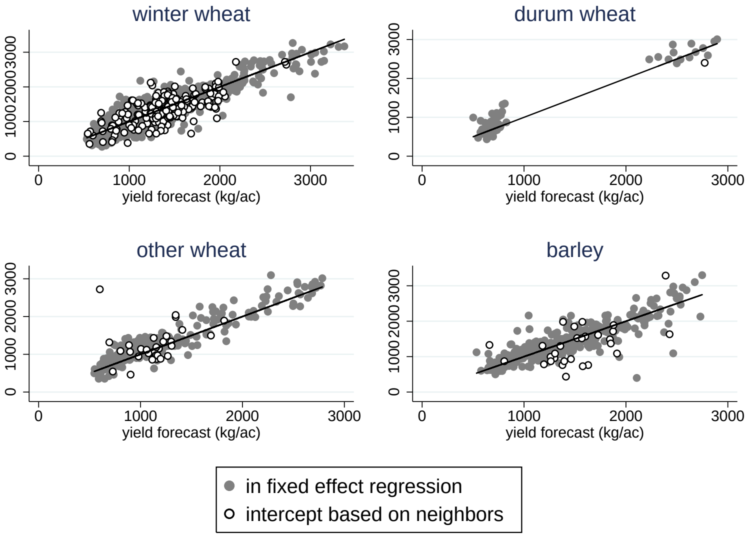
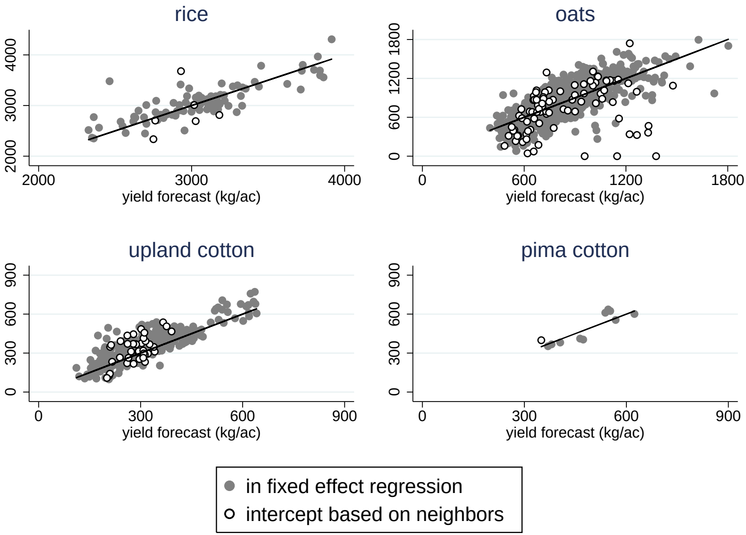
Yield forecasts

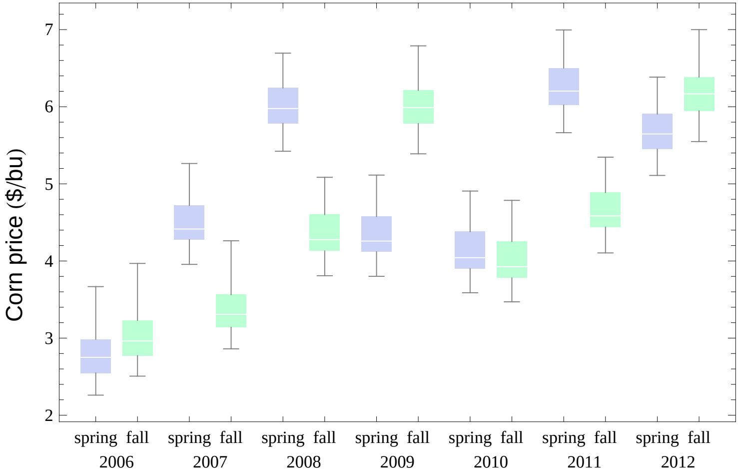


Corn, soybeans
Cotton

Yield forecasts



Corn Prices



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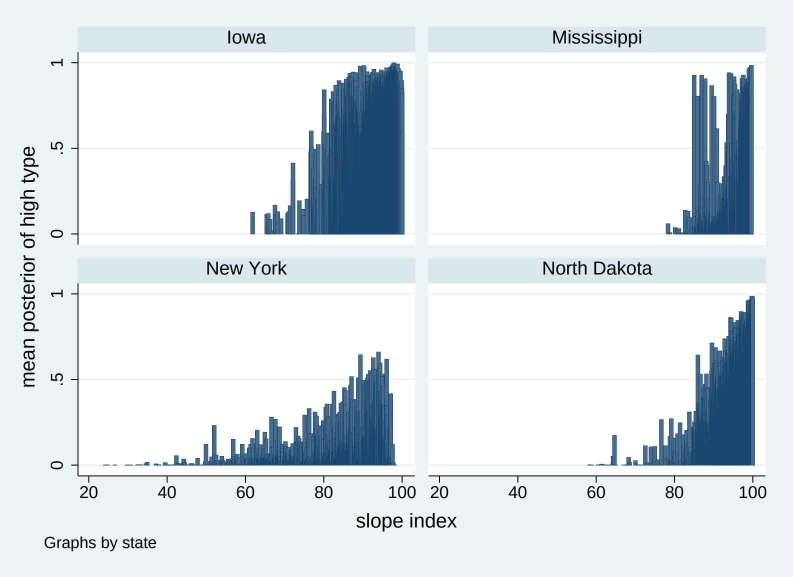
Posteriors



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Elasticity estimates with different models of returns

Acreage elasticity	0.3009	0.3792	0.1315	0.1649
	(0.1149)	(0.1330)	(0.1556)	(0.1652)
Caloric elasticity	0.2951	0.3773	0.1322	0.1676
	(0.1102)	(0.1303)	(0.1568)	(0.1686)
Price forecasts based on	planting season futures		futures from prev. fall	
Costs per acre are	proportional to yields	flat within region	proporitional to yields	flat within region

All models feature two unobservable types, two periods of state dependence, first differences with instruments, and $\beta = .9$. Standard errors in parentheses allow for arbitrary correlation within each year.

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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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Arcidiacono and Miller's Lemma

Arcidiacono and Miller's Lemma

Under conditional independence, there exists a function ψ such that

$$V(x) - v_a(x) = \sigma \psi_a(\mathbf{p}(x); G).$$

- Although only introduced by Arcidiacono and Miller (2011), this is a direct consequence of the Hotz-Miller inversion (Hotz and Miller, 1993).
- With logit errors,

$$V(x) - v_a(x) = -\sigma \log(p_a(x)) + \gamma$$

where γ is Euler's gamma.

A very useful equation

- From the definition of the conditional value function:

$$\pi_a = v_a - F_a V$$

- From Arcidiacono and Miller's Lemma:

$$v_a = V - \sigma\psi_a$$

- Combining the two,

$$\pi_a = V - \beta F_a V - \sigma\psi_a$$

- We can understand almost all the differences between the identification cases by looking at this equation.

Standard CCP Estimation

Proposition 1

Suppose (σ, β, G) are known. For some action J and all states x, suppose the profits $\pi(J, x)$ are known or strongly normalized. Then, conditional choice probabilities and the transition function F identify π.

Standard CCP Estimation

- Our equation:
$$\pi_a = V - \beta F_a V - \sigma\psi_a$$

- Idea for proof:
  - use normalized action to solve for V
    $V = (I - \beta F_a)^{-1} (\pi_J + \sigma\psi_J)$
  - with V, can solve for profits for other actions

Estimation with Value Function Measurement

Proposition 2

Suppose (β, G) are known. For some pair (J, x), suppose the (cardinal) profits $\pi_J(x)$ are known. Then, the value function, conditional choice probabilities, and the transition function F identify π.

- Here, some flow profits must be measured. Not normalized.
- σ cannot be normalized here.

Estimation with Value Function Measurement

- Our equation:
$$\pi_a = V - \beta F_a V - \sigma \psi_a$$

- If σ is known, the proof is trivial. We no longer need the normalization here, because now the RHS is observable.

- Note that σ can be estimated using this equation for the action a with flow profit information.

Using average flow profit information

- We rely on information on flow profits to identify σ
- It's hard to think of examples where $\pi_J(x)$ is available.
- In our application, $E[\pi_J(x)]$ – the average profits of an action averaged over states – is available. For example, this is the average returns to cropland.
- We can estimate σ as follows:

$$\sigma = \frac{1}{E[\psi_J(x)]}\left[E[V(x)] - \beta E\left[\sum_{x' \in X} \Pr(x'|J,x)\, V(x')\right] - E[\pi_J(x)]\right]$$

Estimation with value functions and unobserved states

- Suppose the profit function breaks down as follows:

$$\pi_{at}(k) = \tilde{\pi}_a(k, w_t) + \xi_a(k, \omega_t)$$

Proposition 3

Suppose (β, G) are known. For some pair (J, k), suppose the (cardinal) profits $\tilde{\pi}_J(k, w_t)$ are known for all t. Then, the value function, conditional choice probabilities, and the transition function F^k identify $\tilde{\pi}$.

- In this setting, the value function $V_t(k)$ and CCP's $\mathbf{p}_t(k)$ may be estimated for each time period in a first stage.

Estimation with value functions and unobserved states

- In this context, our equation becomes:

$$\pi_{a,t} = V_t - \beta F_a^k V_{t+1} - \sigma \psi_{a,t} + \varepsilon_{a,t}^V$$

- Again, the RHS is observable, so identification is intuitive.
- The expectational error term means we might not be able to estimate $\pi_{a,t}$ consistently for a given t – this is why the identification result is written in terms of a $\pi(w_t)$ function, so that we can average expectational error terms out over time.

Estimation with observed states, without value functions

Proposition 4

Suppose (β, G, σ) are known.
For some action J. Suppose the profits $\pi_{Jt}(k)$ for all t and k are known (or strongly normalized).
Furthermore, suppose that some action a^* is a renewal action, meaning that $F(k'|a^*, k)$ does not depend on k.
Then conditional choice probabilities and the transition function F^k identify $\tilde{\pi}$.

Estimation with observed states, without value functions

- In this context, our equation becomes:

$$\pi_{a,t} = V_t - \beta F_a^k V_{t+1} - \sigma \psi_{a,t} + \varepsilon_{a,t}^V$$

- We don't observe the V's on the RHS here, and we can't solve them out with a matrix inversion because V_t and V_{t+1} may be different.

Estimation with observed states, without value functions

$$\pi_{a,t} = V_t - \beta F_a^k V_{t+1} - \sigma\psi_{a,t} + \varepsilon_{a,t}^V$$

- Take differences of this equation for action a and normalized renewal action J:

$$\pi_{a,t} = \pi_{J,t} - \beta \left(F_a^k - F_J^k\right) V_{t+1} - \sigma\left(\psi_{a,t} - \psi_{J,t}\right) + \varepsilon_{a,t}^V - \varepsilon_{J,t}^V$$

- Use Arcidiacono and Miller Lemma:

$$\pi_{a,t} = \pi_{J,t} - \beta \left(F_a^k - F_J^k\right)\left(v_{J,t+1} + \sigma\psi_{J,t+1}\right) - \sigma\left(\psi_{a,t} - \psi_{J,t}\right) + \varepsilon_{a,t}^V - \varepsilon_{J,t}^V$$

- Noting that renewal action returns individual state k to same value at $t+2$:

$$\pi_{a,t} = \pi_{J,t} - \beta \left(F_a^k - F_J^k\right)\left(\pi_{J,t+1} + \sigma\psi_{J,t+1}\right) - \sigma\left(\psi_{a,t} - \psi_{J,t}\right) + \varepsilon_{a,t}^V - \varepsilon_{J,t}^V$$

Estimation with observed states, without value functions

$$\pi_{a,t} = \pi_{J,t} - \beta \left(F_a^k - F_J^k \right) \left(\pi_{J,t+1} + \sigma \psi_{J,t+1} \right) - \sigma \left(\psi_{a,t} - \psi_{J,t} \right) + \varepsilon_{a,t}^V - \varepsilon_{J,t}^V$$

- Say $\pi_{J,t} = 0$ for all t, we can write this as a regression equation:

$$\psi_{a,t} - \psi_{J,t} + \beta \left(F_a^k - F_J^k \right) \psi_{J,t+1} = \sigma^{-1} \left(\pi_{a,t} + \varepsilon_{a,t}^V - \varepsilon_{J,t}^V \right)$$

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Moments from V

Arcidiacono and Miller's Lemma for the $k = 1$ and $k = 2$:

$$
\begin{aligned}
V_t(1) &= \sigma\psi_{other,t}(1) + \sigma\theta_{other,1} + R_{other,t} + \xi_{other,t}(1) + \beta E_t V_{t+1}(2 \\
V_t(2) &= \sigma\psi_{other,t}(2) + \sigma\theta_{other,2} + R_{other,t} + \xi_{other,t}(2) + \beta E_t V_{t+1}(2
\end{aligned}
$$

Define moment, averaging out the ξ's and ε^V's:

$$
\begin{aligned}
m_{V,other,1,2} &\equiv \psi_{other,t}(2) - \psi_{other,t}(1) + E\left[\frac{V_t(1)-V_t(2)}{\sigma}\right] \\
&= \alpha_{0,other,1} - \theta_{0,other,2}
\end{aligned}
$$

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