Groundwater usage: Game theory and empirics

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Human Dimensions of Environmental Risks
Monte Verità, Ascona, Switzerland

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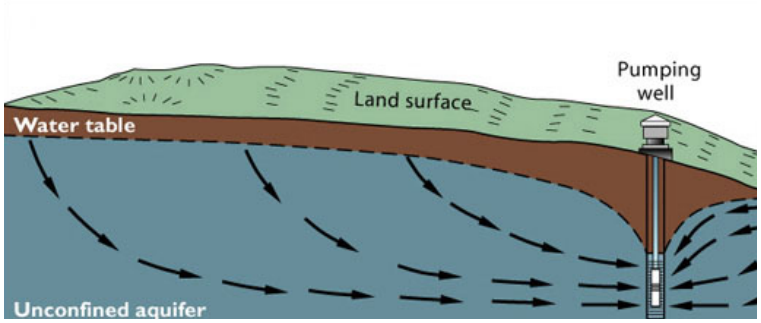
Structure of groundwater usage: *Common-pool resource dilemma*

Shared

Individual decisions

Key points:

- Individual primarily values what he can *extract*
- Private cost does not reflect *'public cost/ externalities'*



Groundwater situation in the High Plains Aquifer

- One of the largest aquifer systems in the world.
- 8% of the aquifer depleted. [Scanlon et al., 2012]
- 35% of the southern HPA exhausted in the next 30 years. [Scanlon et al., 2012]

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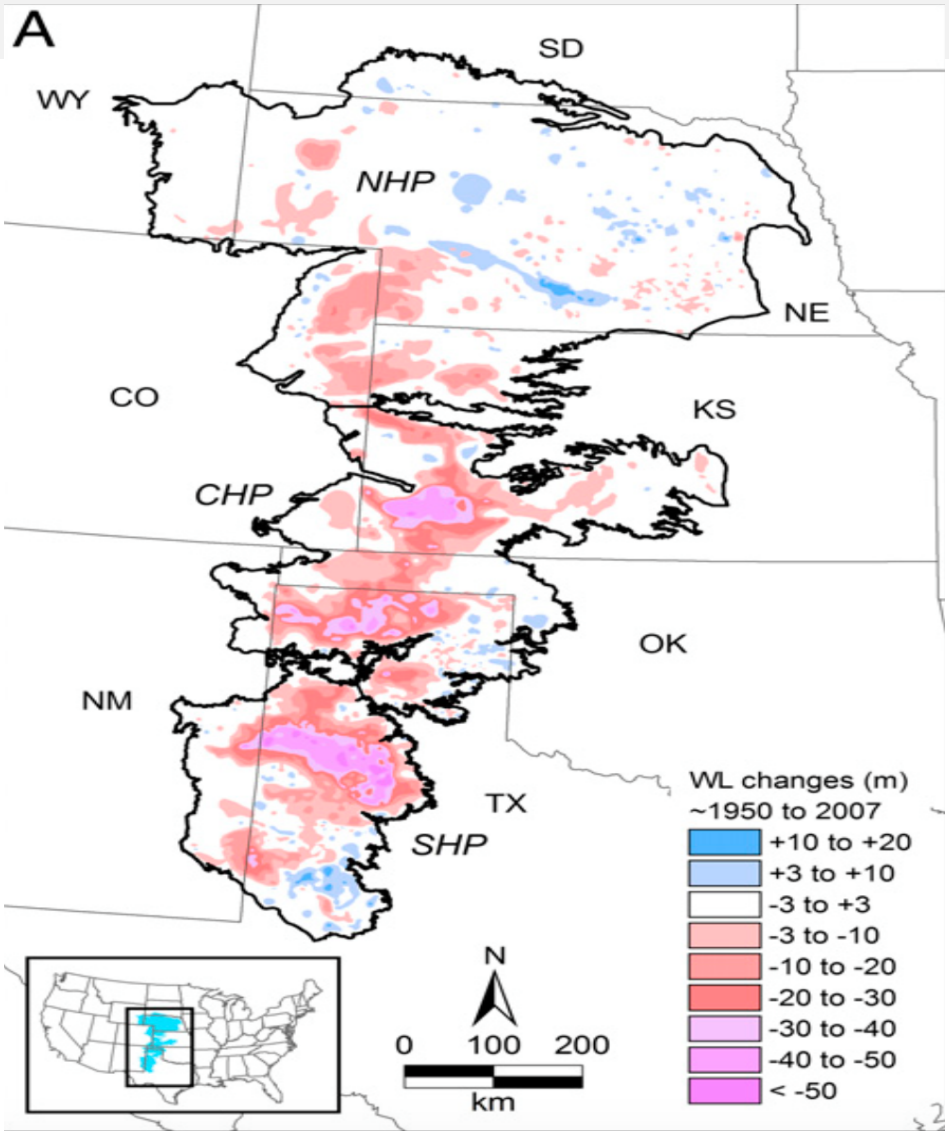

One research question for today

Q : How does (micro) farmers' 'strategic' interactions relate with patterns of (macro) common-pool exploitation?

Structure of talk:

1. Literature review: Game theory vs. case studies
2. Empirical analysis of micro-behavior
3. Counterfactuals

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- Hotelling [1931, p. 138]: products/supplies from shared resource *"... are [sold] $\underbrace{\textit{too cheap}}_{*}$ and are begin sold $\underbrace{\textit{too rapidly}}_{***}$"*
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  - Repeated game [Shapley, 1953]
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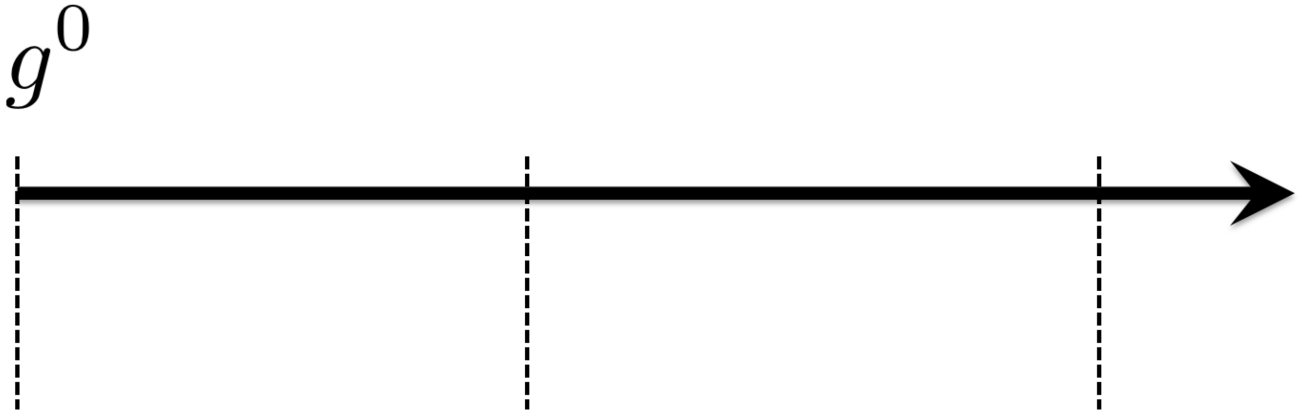

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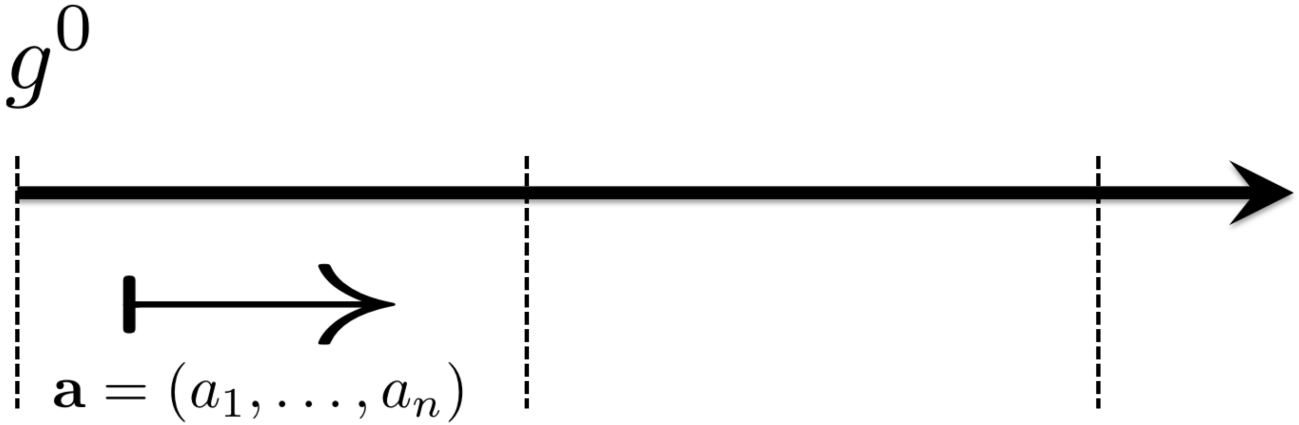

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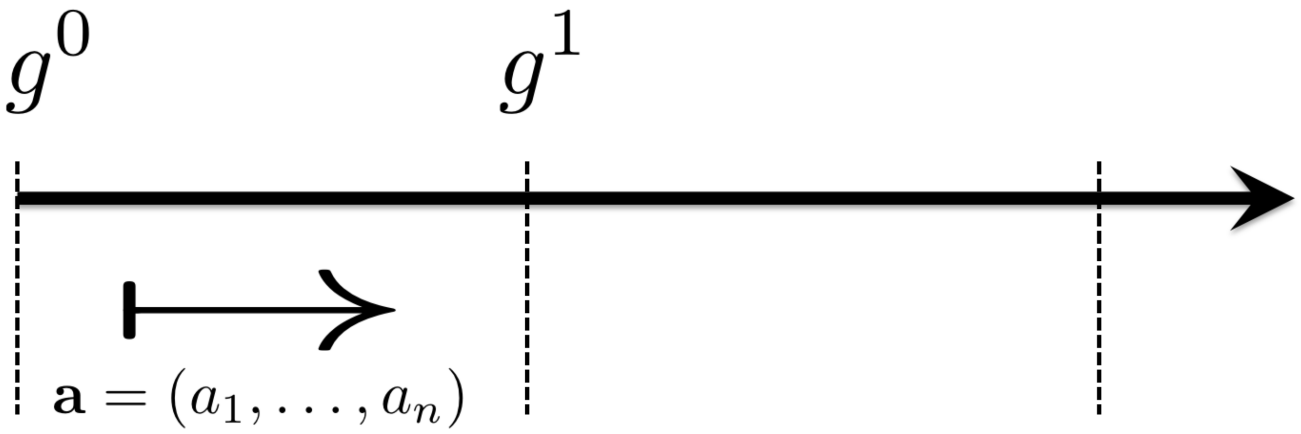

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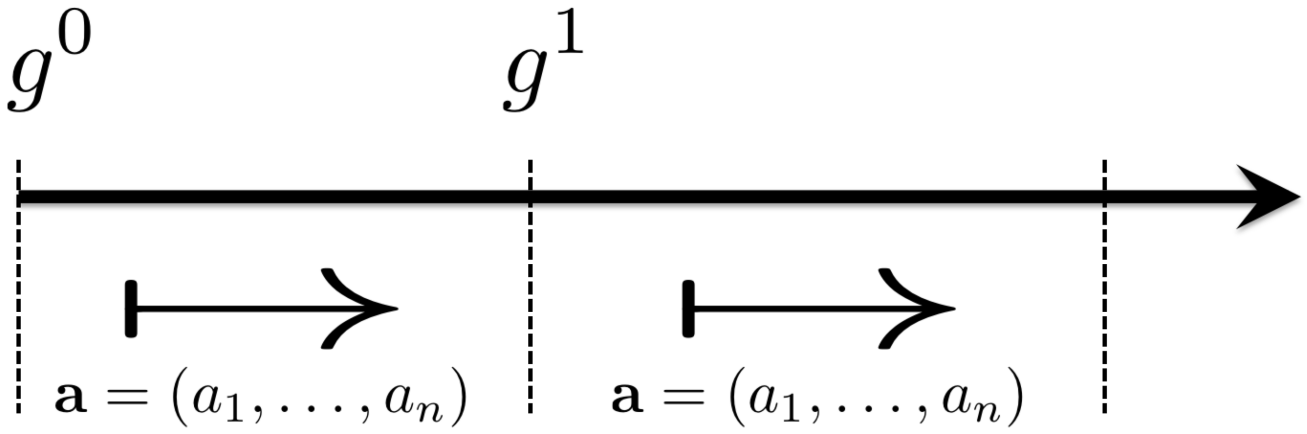

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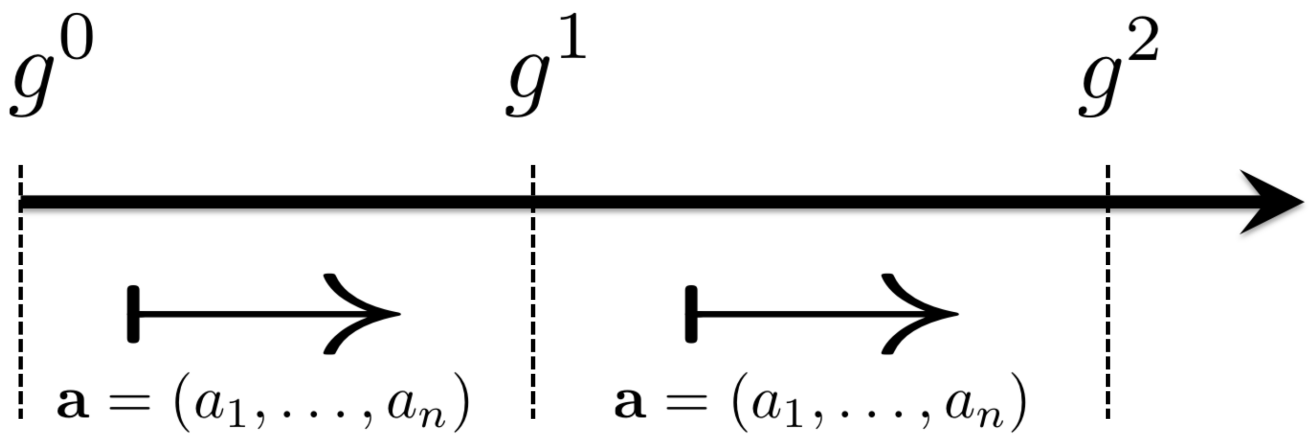

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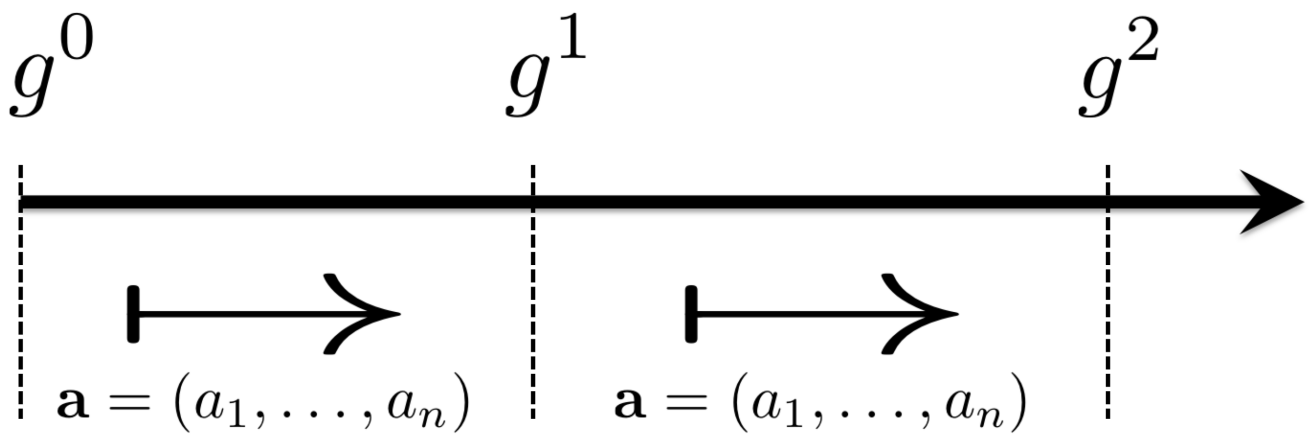
    Prediction: over-usage — the more a user conserves, the more others will over-exploit



Predictions: Game theory vs. case studies

Observation: the game-theoretic literature predicts strategic substitutes / free-riding / negative interaction effects

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- Same observation made in several extensions, including Dutta and Sundaram [1993], Negri [1989], Mirman and To [2005], Mirman and Santugini [2014], among others

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... positive interaction effects

- Kerr [1991, Shared geothermal reservoir]: cited that firms observing rivals over-use incites further over-usage

- Alexander [1982, Sri Lankan fishery]: fisherman react to others' over-capture by also over-capturing

- Empirical evidence for *race to fish*: **over-fish** in anticipation of rival fisherman also **over-fishing**
- Possible 20% increase in annual industry revenue if policies are designed around strategic interactions

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Negative vs. **Positive** interaction effects?

Difference with our study:

- We can directly estimate interaction effects
- We do not rely on latent variable estimator for stock, but include groundwater levels directly
- *No 'race to fish' effect: irrigation farming is a more consistent decision*

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Empirical analysis

Game theoretical predictions $\overset{?}{\longleftrightarrow}$ Data

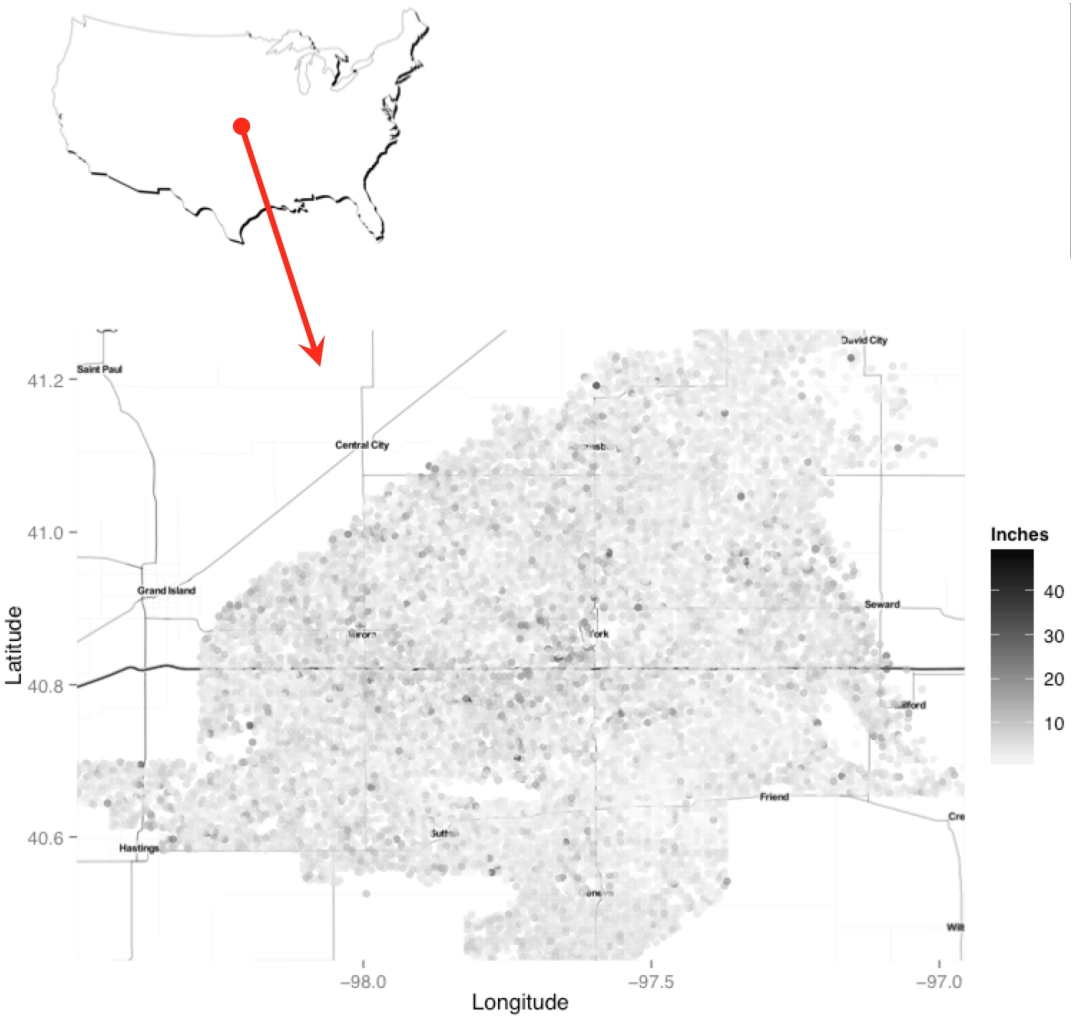
Our large-scale dataset

Individual usage data

- Upper Big Blue (UBB) District, NE:
  - 15% of NE agriculture
  - 2% of US agriculture
- Well-per-well extraction information for 2008 – 2014
  - ∼100,000 data points

Geological data

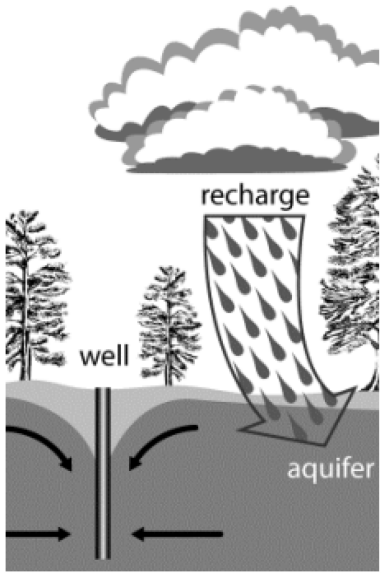
- Groundwater tables across UBB for 2008 – 2014
- Individual characteristics: soil type, specific yield, evapotranspiration, precipitation, yearly rainfall, and transmissivity



Structure of empirical data

- **Individual attributes, $\mathbf{X}_i$:** land-size (l_i), well-depth (d_i), transmissivity (α_i), soil-type (s_i)
- **Seasonal attributes, $\mathbf{Y}^t$:** rainfall (R^t) & temp. (T^t)
- **Individual & seasonal attributes, $\mathbf{G}_i^t$:** groundwater (G_i^t) and changes in levels ($\Delta G_i^t = G_i^t - G_i^{t-1}$)
- **Interaction effects:** i's water-usage influenced by neighbors' (N_i) water-usage

$$\overline{w}_{N_i}^t = \frac{1}{|N_i|} \sum_{j \in N_i} w_j^t$$



Regression equation:

$$w_i^t = \gamma_i + \beta^x \cdot \mathbf{X}_i + \beta^y \cdot \mathbf{Y}_i + \beta^g \cdot \mathbf{G}_i^t + J \cdot \overline{w}_{N_i}^t + \varepsilon_{it}$$

$$\varepsilon \sim \mathcal{N}(0, \sigma^2)$$

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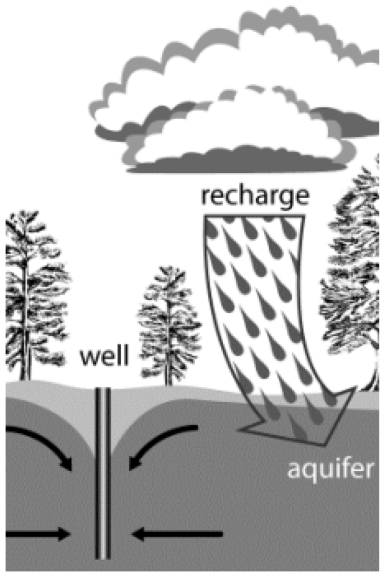

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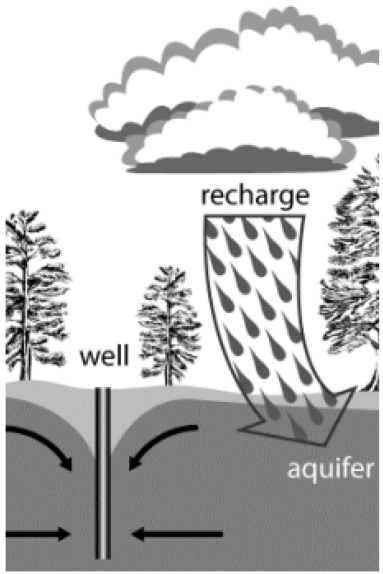

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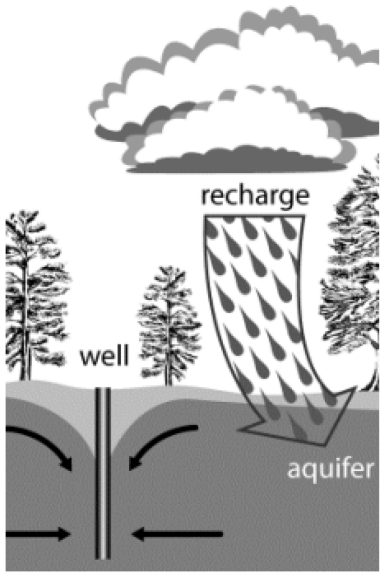

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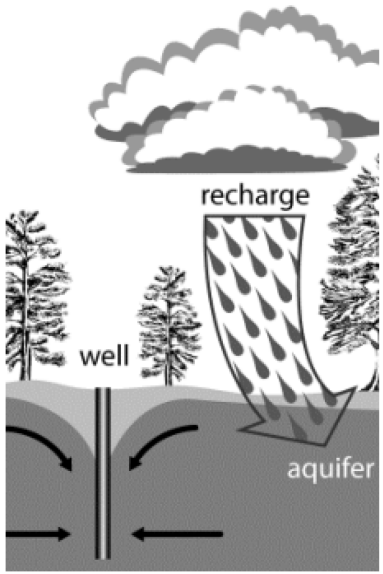

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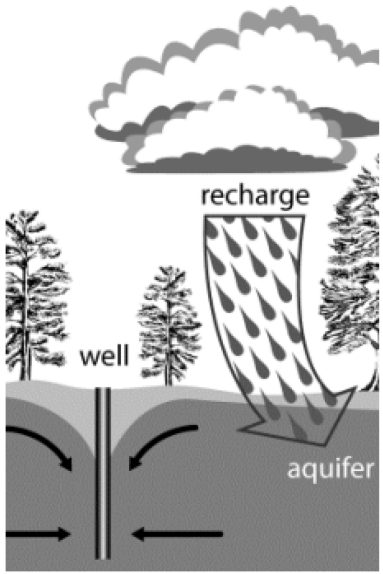

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(1/2) Strategy to handle endogeneity

- a.k.a. reflection problem [Manski, 1993]: neighbors affect neighbors
  - $w_i^t = \cdots + J_i \cdot \overline{w}_{N_i}^t \quad \rightarrow J_i$ is biased

We use Bramoullé et al. [2009, Proposition 1] to identify J_i:

- Network of farmers is **irreducible**
  - (any node reachable in finite # steps)
- Network is **transitive**, i.e., $j \in N_i$ does not imply $i \in N_j$

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Two-stage regression, as suggested by Bramoullé et al. [2009]

(1) Regression to identify (exogenous) $\overline{w}_i^t$:

- Define $\mathbf{A}$ be the $N \times N$ network of farmers
- Let $\mathbf{Z}_i^t = (\mathbf{X}_i, \mathbf{Y}^t, \mathbf{G}_i^t)$ be collection of attributes
- Then $(\mathbf{A}^2\mathbf{Z}_i^t, \mathbf{A}^3\mathbf{Z}_i^t, \ldots)$ are valid instruments for identification

... i's neighbors-neighbors' (and so forth) attributes do not directly affect i's water-usage

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(1) Regression to identify (exogenous) $\overline{w}_i^t$:

- Define $\mathbf{A}$ be the $N \times N$ network of farmers
- Let $\mathbf{Z}_i^t = (\mathbf{X}_i, \mathbf{Y}^t, \mathbf{G}_i^t)$ be collection of attributes
- Then $\left(\mathbf{A}^2\mathbf{Z}_i^t, \mathbf{A}^3\mathbf{Z}_i^t, \dots\right)$ are valid instruments for identification

... i's neighbors-neighbors' (and so forth) attributes do not directly affect i's water-usage

(2) Include the identified $\widetilde{\overline{w}}_i^t$ to explain w_i^t

Empirical results $(N = 95,256)$

	(Neighbor model)	(Controls model)	(Full model)
$\text{Water}^t_{N_i}$ (< 0)	0.6715^{***}		0.6934^{***}
	(0.006)		(0.016)
Rain^t (< 0)	-0.0178^{***}		0.0015
	(0.0037)		(0.012)
Temperature^t (> 0)		0.0169^{***}	0.0082^{**}
		(0.003)	(0.004)
Land-size_i (< 0)	-0.0766^{***}		-0.1211^{***}
	(0.0040)		(0.005)
Well Depth_i (< 0)		-0.0142^{**}	0.0195^{***}
		(0.007)	(0.005)
Transmissivity_i (< 0)		-0.0124^{*}	0.0017
		(0.004)	(0.004)
Groundwater^t_i (< 0)		-0.3446^{***}	-0.064^{***}
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(1/2) Who is most prone to positive interaction effects?

- Regression estimated *average* effect, $\overline{J} = 0.6934^{***}$
  $\rightarrow$ finer-grained analysis?

$$\text{Regression:} \qquad w_i^t = \gamma_i + \cdots + J_i + \cdots$$

- Allow γ_i and J_i to be drawn from a joint distribution:

$$\begin{array}{ll} i\text{'s usage} & \gamma_i = \beta_\gamma + \eta_i^\gamma \\ \text{Neighborhood} & J_i = \beta_J + \eta_i^J \end{array} \quad , \quad \begin{pmatrix} \eta_i^\gamma \\ \eta_i^J \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\gamma^2 & \sigma_\gamma \sigma_J \\ \sigma_\gamma \sigma_J & \sigma_J^2 \end{pmatrix} \right).$$

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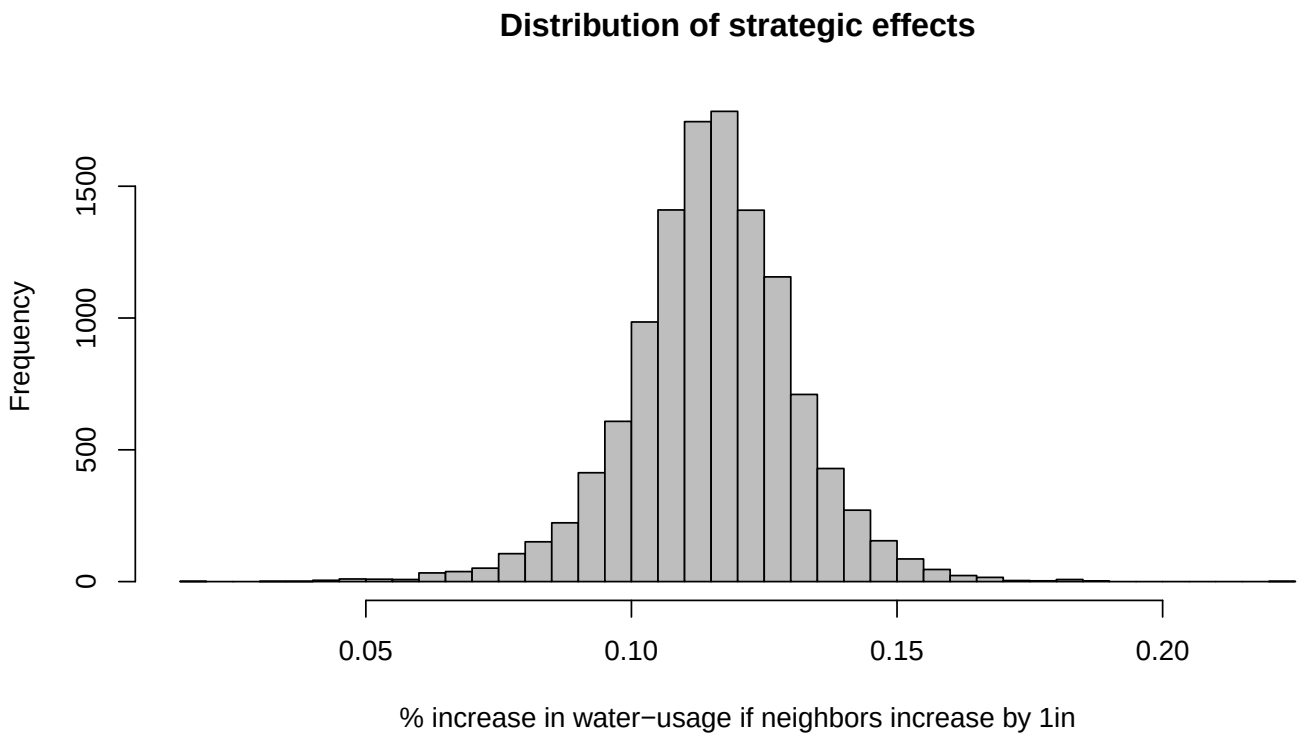
- **Results: higher water-users correlated with stronger reaction to neighbors**

$$Correlation\,(\gamma_i, J_i) = \sigma_\gamma \sigma_J = 0.71$$

- General evidence that interaction effects work to the detriment of groundwater levels



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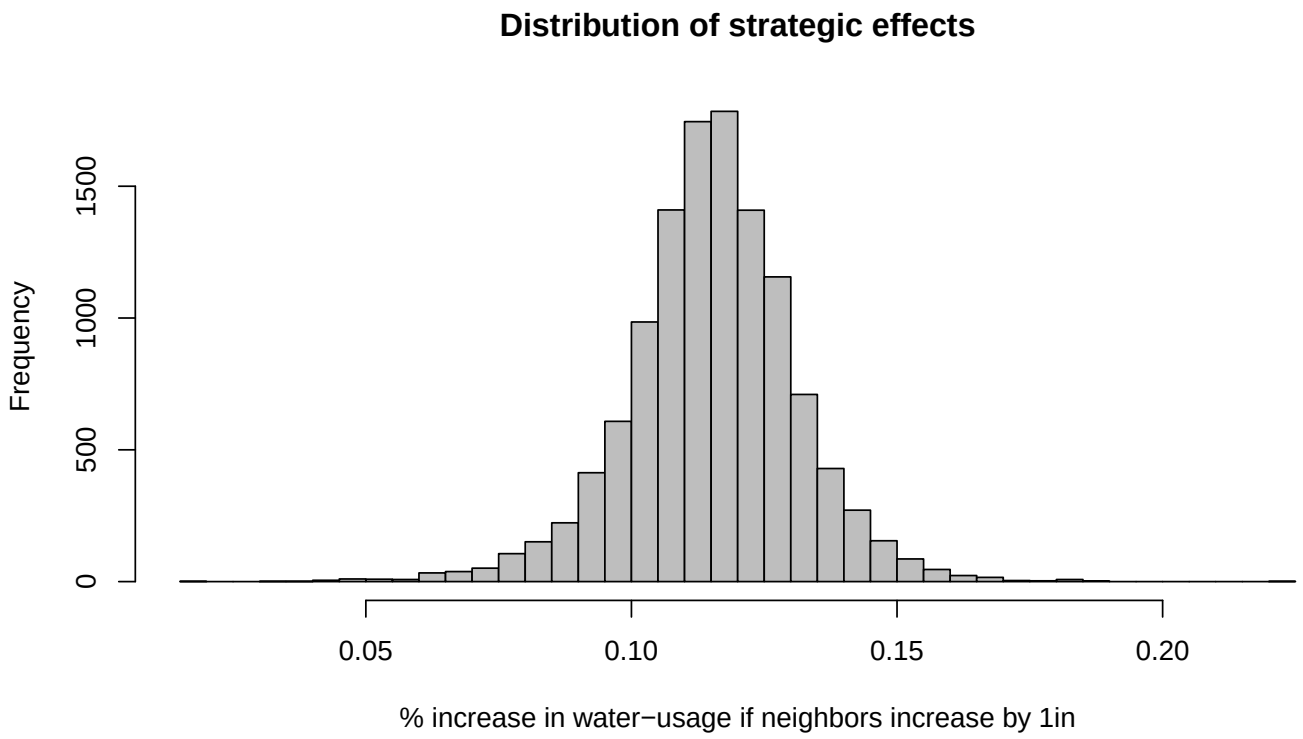

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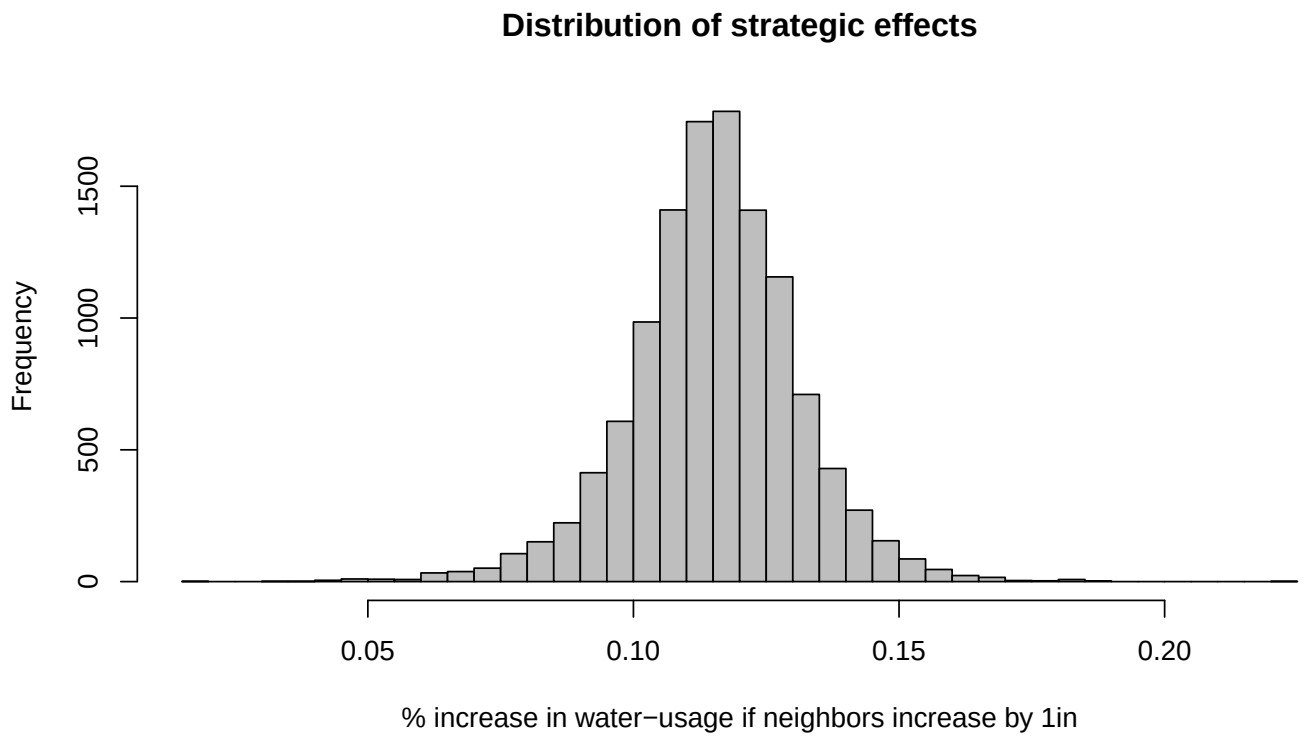

Counterfactuals (briefly)

How important are neighborhood effects for policy design?

Counterfactual design

- Current discussion: **farm-assistant technology**
  - $\rightarrow$ tech. influences a farmer's decision, & not neighbors
- Implementation: prediction groundwater usage if neighborhood effect by p-percent

$$J_i^* = (1 - p) \cdot J_i$$

- $p = 0 \rightarrow$ **to baseline, no-intervention**
- $p = 1 \rightarrow$ **farms operate solely on technology**

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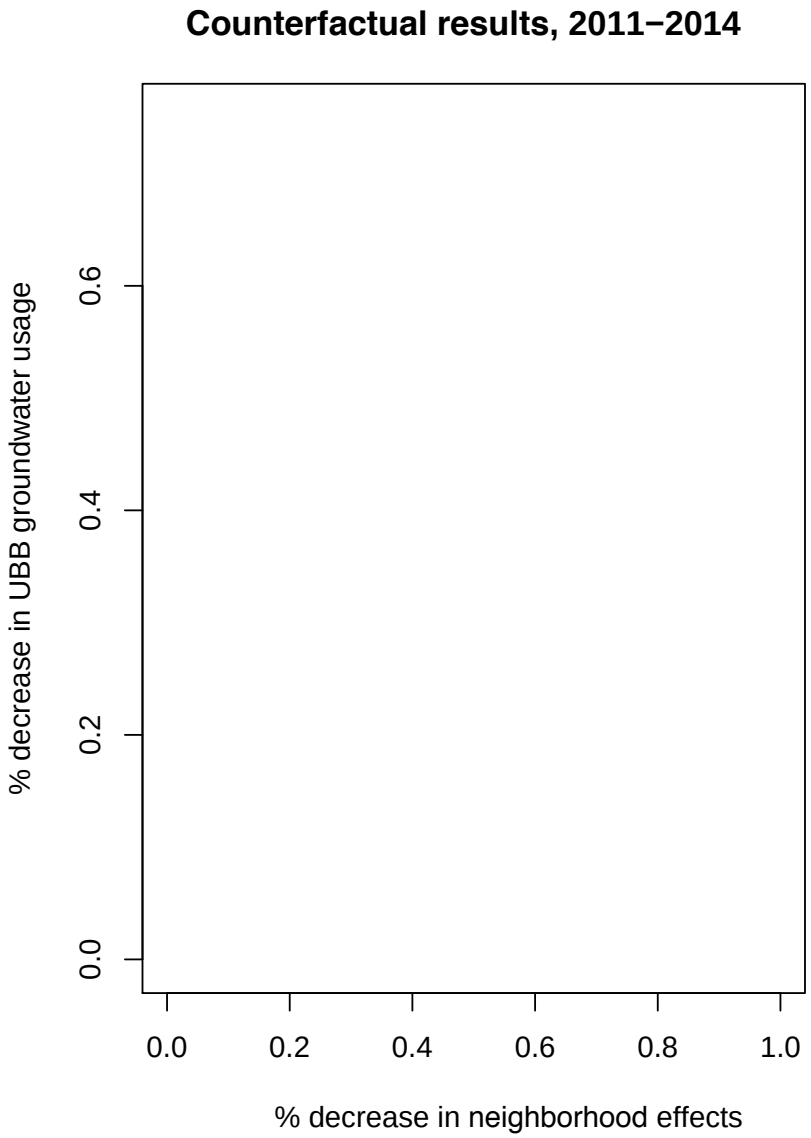
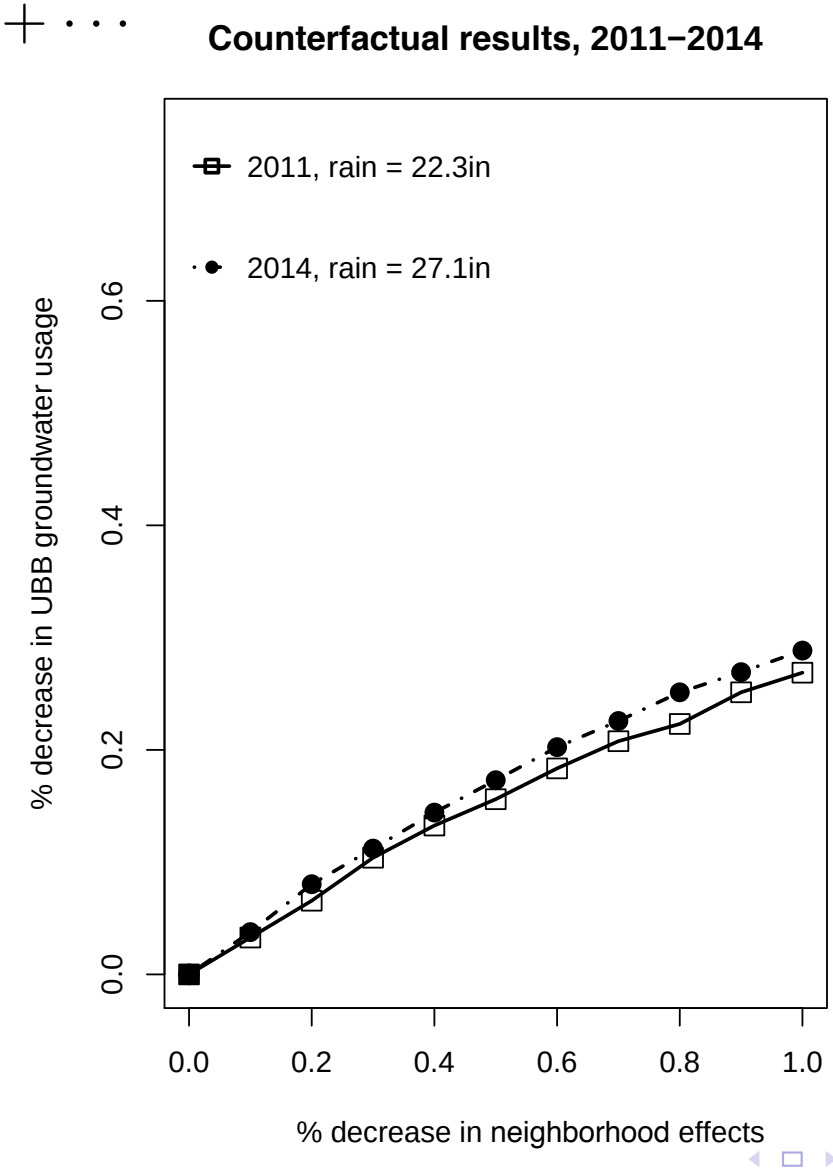
Counterfactual results

$w_i^t = \cdots + J_i^* \cdot \overline{w}_i^t$ -



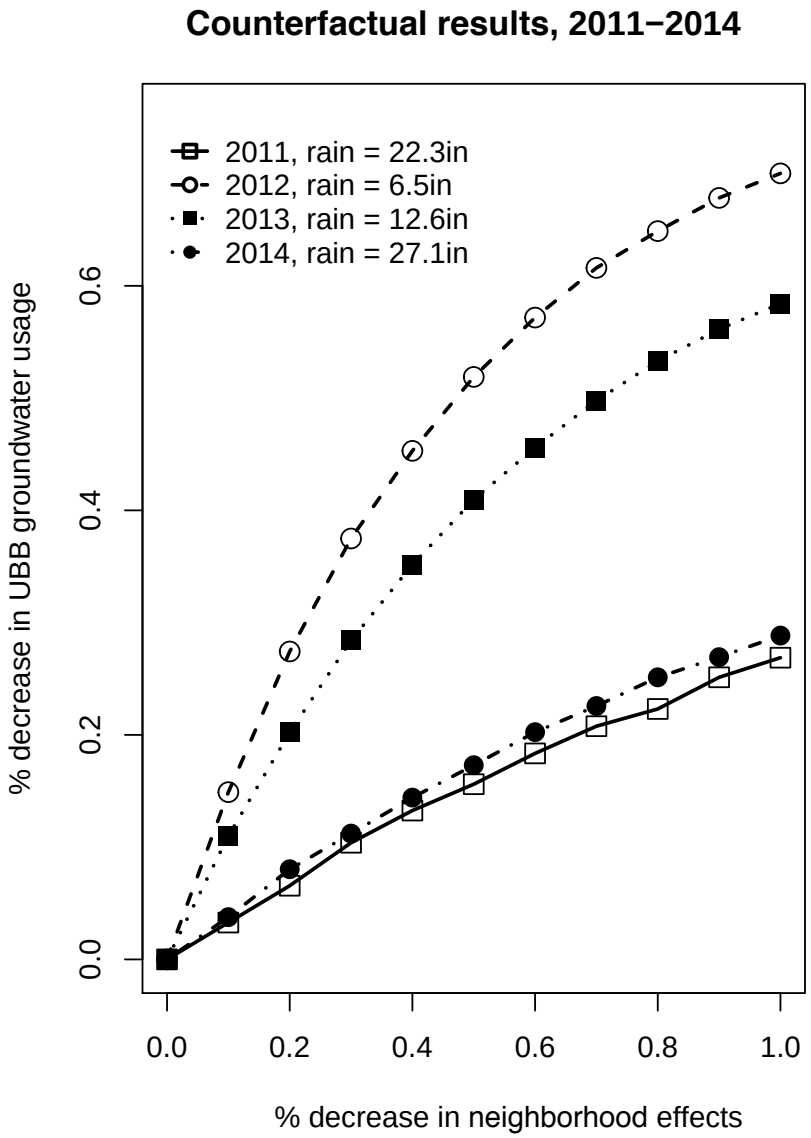
Counterfactual results

$$w_i^t = \cdots + J_i^* \cdot \overline{w}_i^t + \cdots$$



Counterfactual results

$$w_i^t = \cdots + J_i^* \cdot \overline{w}_i^t \text{ -}$$



Future work

- Why do farmers exhibit positive interaction effects?
  - Which game-theoretic axioms do we critique? (Completeness)
    - ... best-reply convergence to equilibrium [Dindoš and Mezzetti, 2006, Jensen, 2010]
  - Reciprocity [Fehr and Schmidt, 2006], uncertainty heuristics [Tversky and Kahneman, 1974], imitation...
- Richer counterfactual designs
  - Quota policies, forecast groundwater depletion trends based on different policies, etc.

→ **Thank you!**

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