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]
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] too cheap and are begin sold too rapidly”

- Levhari and Mirman [1980]: first game-theoretic model capturing how resource users behave as they anticipate their participation in depletion
  - Repeated game [Shapley, 1953]
  - Usage ‘today’ decreases stock levels ‘tomorrow’
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![Diagram](image)
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  - Repeated game [Shapley, 1953]
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    **Prediction:** over-usage — the more a user conserves, the more others will over-exploit

\[
g^0 \quad \quad \quad g^1 \quad \quad \quad g^2
\]

\[
a = (a_1, \ldots, a_n)
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Prediction: Game theory vs. case studies

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

\[ \frac{\partial (\text{my optimal action})}{\partial (\text{others' actions})} < 0 \]

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

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- We can directly estimate interaction effects
- We do not rely on latent variable estimator for stock, but include groundwater levels directly
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Empirical analysis

Game theoretical predictions $\leftrightarrow$ 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
Empirical analysis

Structure of empirical data

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

\[
\bar{w}^t_{N_i} = \frac{1}{|N_i|} \sum_{j \in N_i} w_j^t
\]

Regression equation:

\[
w_i^t = \gamma_i + \beta^x \cdot X_i + \beta^y \cdot Y_i + \beta^g \cdot G^t_i + J \cdot \bar{w}^t_{N_i} + \epsilon_{it}
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\epsilon \sim \mathcal{N}(0, \sigma^2)
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(1/2) Strategy to handle endogeneity

- a.k.a. reflection problem [Manski, 1993]: neighbors affect neighbors
  \[ w_i^t = \cdots + J_i \cdot w_{N_i}^t \quad \Rightarrow \quad J_i \text{ is biased} \]

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) $\bar{w}_t^i$:
   - Define $A$ be the $N \times N$ network of farmers
   - Let $Z_t^i = (X_t^i, Y_t^i, G_t^i)$ be collection of attributes
   - Then $(A^2Z_t^i, A^3Z_t^i, \ldots)$ 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 $\tilde{w}_t^i$ to explain $w_t^i$
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## Empirical results $(N = 95, 256)$

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<th>(Controls model)</th>
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Empirical results \((N = 95, 256)\)

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<td>0.6934***</td>
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<td>(0.012)</td>
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<td>−0.064***</td>
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<td>0.6934*** (0.016)</td>
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<td>(\text{Rain}^t) (&lt; 0)</td>
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<td>(\text{Temperature}^t) (&gt; 0)</td>
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<td>(\text{Land-size}_i) (&lt; 0)</td>
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<td>−0.1211*** (0.005)</td>
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<td>(\text{Well Depth}_i) (&lt; 0)</td>
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Fixed-effect \(R^2\) \(0.24\) \(0.09\) \(0.26\)
Conditional \(R^2\) \(0.63\) \(0.50\) \(0.66\)
### Empirical results \((N = 95,256)\)

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Fixed-effect \(R^2\) 0.24 0.09 0.26
Conditional \(R^2\) 0.63 0.50 0.66
Empirical results  \((N = 95, 256)\)

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### Empirical analysis

#### Results

**Empirical results**  \((N = 95, 256)\)

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(*N* = 95, 256)

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\( N = 95, 256 \)

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<tr>
<td>Water(_t) (_N_1) (&lt; 0)</td>
<td>0.6715(***) (0.006)</td>
<td></td>
<td>0.6934(***) (0.016)</td>
</tr>
<tr>
<td>Rain(_t) (&lt; 0)</td>
<td>-0.0178(***) (0.0037)</td>
<td></td>
<td>0.0015</td>
</tr>
<tr>
<td>Temperature(_t) (&gt; 0)</td>
<td></td>
<td>0.0169(***) (0.003)</td>
<td>0.0082(**) (0.004)</td>
</tr>
<tr>
<td>Land-size(_i) (&lt; 0)</td>
<td>-0.0766(***) (0.0040)</td>
<td></td>
<td>-0.1211(***) (0.005)</td>
</tr>
<tr>
<td>Well Depth(_i) (&lt; 0)</td>
<td>-0.0142(**) (0.007)</td>
<td></td>
<td>0.0195(***) (0.005)</td>
</tr>
<tr>
<td>Transmissivity(_i) (&lt; 0)</td>
<td></td>
<td>-0.0124(*)) (0.004)</td>
<td>0.0017</td>
</tr>
<tr>
<td>Groundwater(_i) (_t) (&lt; 0)</td>
<td>-0.3446(***) (0.008)</td>
<td>-0.064(***) (0.004)</td>
<td></td>
</tr>
<tr>
<td>ΔGroundwater(_i) (_t) (&lt; 0)</td>
<td></td>
<td>0.1350(***) (0.003)</td>
<td>0.0195(***) (0.003)</td>
</tr>
</tbody>
</table>

Fixed-effect \(R^2\) | 0.24 | 0.09 | 0.26 |
Conditional \(R^2\) | 0.63 | 0.50 | 0.66 |
(1/2) Who is most prone to positive interaction effects?

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

Regression:

$$w_i = \gamma_i + \cdots + J_i + \cdots$$

- Allow $\gamma_i$ and $J_i$ to be drawn from a joint distribution:

\begin{align*}
\text{i’s usage} & \quad \gamma_i = \beta_{\gamma} + \eta_i^\gamma, \quad \begin{pmatrix} \eta_i^\gamma \\ \eta_i^J \end{pmatrix} \sim N \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{\gamma}^2 & \sigma_{\gamma} \sigma_{J} \\ \sigma_{\gamma} \sigma_{J} & \sigma_{J}^2 \end{pmatrix}.
\end{align*}

- $\sigma_{\gamma} \sigma_{J}$ indicates correlation between the two parameters
(1/2) Who is most prone to positive interaction effects?

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

Regression:

$$w_i^t = \gamma_i + \cdots + J_i + \cdots$$

- Allow $\gamma_i$ and $J_i$ to be drawn from a joint distribution:

$$\gamma_i = \beta_\gamma + \eta_i^\gamma, \quad \left( \eta_i^\gamma \right) \sim \mathcal{N} \left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\gamma^2 & \sigma_\gamma \sigma_J \\ \sigma_\gamma \sigma_J & \sigma_J^2 \end{pmatrix} \right).$$

$$J_i = \beta_J + \eta_i^J,$$

$i$'s usage

Neighborhood

- $\sigma_\gamma \sigma_J$ indicates correlation between the two parameters
(1/2) Who is most prone to positive interaction effects?

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

Regression: $w_i^t = \gamma_i + \cdots + J_i + \cdots$

- Allow $\gamma_i$ and $J_i$ to be drawn from a joint distribution:

  $i$’s usage $\gamma_i = \beta_\gamma + \eta_i^\gamma$, $J_i = \beta_J + \eta_i^J$, $(\eta_i^\gamma, \eta_i^J) \sim \mathcal{N} ((0, 0), (\sigma_\gamma^2, \sigma_\gamma \sigma_J, \sigma_J^2))$.

- $\sigma_\gamma \sigma_J$ indicates correlation between the two parameters
(1/2) Who is most prone to positive interaction effects?

- Regression estimated *average* effect, $\bar{J} = 0.6934^{***}$
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Regression: \[ w_i^t = \gamma_i + \cdots + J_i + \cdots \]

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  i's \ usage & \quad \gamma_i = \beta_\gamma + \eta_i^\gamma,
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  Neighborhood & \quad J_i = \beta_J + \eta_i^J,
  \quad \left( \eta_i^J \right) \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). 
  \end{align*} \]

- $\sigma_\gamma \sigma_J$ indicates correlation between the two parameters
Empirical analysis

Results

(1/2) Who is most prone to positive interaction effects?

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

Regression:  
$$w_i^t = \gamma_i + \cdots + J_i + \cdots$$

- Allow $\gamma_i$ and $J_i$ to be drawn from a joint distribution:

  - *i*’s usage  
    $\gamma_i = \beta_\gamma + \eta_i^\gamma$  
  - Neighborhood  
    $J_i = \beta_J + \eta_i^J$  

$$\begin{pmatrix} \eta_i^\gamma \\ \eta_i^J \end{pmatrix} \sim \mathcal{N} \left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\gamma^2 & \sigma_\gamma \sigma_J \\ \sigma_\gamma \sigma_J & \sigma_J^2 \end{pmatrix} \right)$$

- $\sigma_\gamma \sigma_J$ indicates correlation between the two parameters
(1/2) Who is most prone to positive interaction effects?

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

Regression: $w_i^t = \gamma_i + \cdots + J_i + \cdots$

- Allow $\gamma_i$ and $J_i$ to be drawn from a joint distribution:

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

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Koch & Nax
Groundwater
May 25th 2017
(2/2) Who is most prone to positive interaction effects?

- Results: higher water-users correlated with stronger reaction to neighbors
  \[ \text{Correlation} \left( \gamma_i, J_i \right) = \sigma_\gamma \sigma_J = 0.71 \]
- General evidence that interaction effects work to the detriment of groundwater levels
(2/2) Who is most prone to positive interaction effects?

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![Distribution of strategic effects](image-url)
Counterfactuals (briefly)

How important are neighborhood effects for policy design?
Counterfactual design

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

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

- $p = 0$ → to baseline, no-intervention
- $p = 1$ → farms operate solely on technology
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Counterfactual results

\[ w_i^t = \cdots + J_i^* \cdot \bar{w}_i^t - \]

Counterfactual results, 2011–2014
Counterfactual results

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

Counterfactual results, 2011–2014

- 2011, rain = 22.3in
- 2014, rain = 27.1in

% decrease in UBB groundwater usage
% decrease in neighborhood effects
Counterfactual results

\[ w_i^t = \cdots + J_i^* \cdot \bar{w}_i^t - \]

Counterfactual results, 2011–2014

- 2011, rain = 22.3in
- 2012, rain = 6.5in
- 2013, rain = 12.6in
- 2014, rain = 27.1in

% decrease in neighborhood effects vs. % decrease in UBB groundwater usage
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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References


