Dynamic Environmental Applications

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Outline

"Measuring the Dynamic Efficiency Costs of Regulators' Preferences: Municipal Water Authorities and the Arid West"
Christopher Timmins (2002)

Groundwater extraction

- In many counties in California, aquifers are the primary water source.
- Groundwater must be pumped to the surface, and the cost depends on the water level. As the aquifer is depleted, the cost of extaction increases.
- There is typically one utility company responsible for the extraction and distribution of water, and rates are controlled by the government.

Dynamic costs

- Because water extraction today makes extraction tomorrow more expensive, it woud not be optimal to set the current price equal to the current cost of extraction.
- Timmins defines a dynamic marginal cost:

$$MC'_{1991} = MC_{1991} + E_{1991}\left[\sum_{t=1992}^{\infty} \beta^{t-1991} \frac{\partial C'_t}{\partial D_{1991}}\right]$$

- However, water in California is typically priced well below marginal cost.

Questions

- How is water priced? (What is the regulator's objective function?)
- How would economic surplus be improved if water were priced efficiently in a static sense? In a dynamic sense?

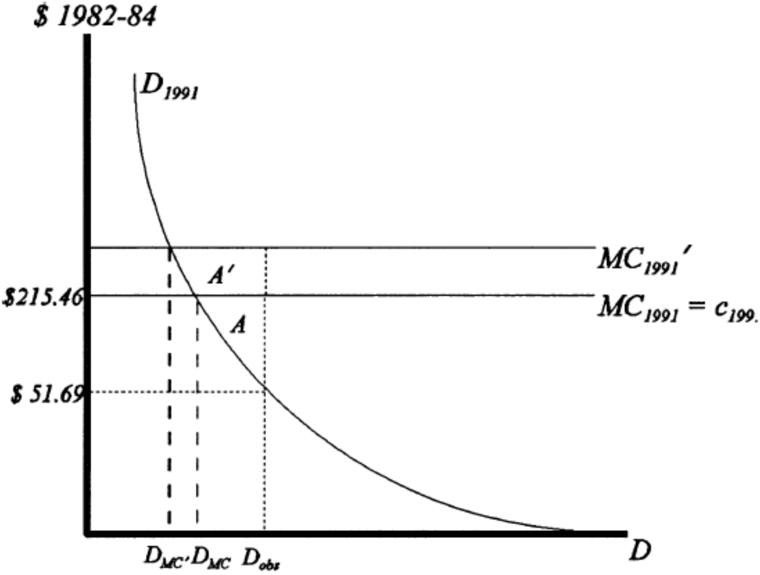


FIGURE 1.

TABLE I

MARGINAL COSTS AND PRICES, AVERAGES BY CITY
(CONSTANT 1982–84 DOLLARS)

City	Obs	$MC_{i,t} - P_{i,t}$	$(MC_{i,t} - P_{i,t})/MC_{i,t}$
Clovis	16	19.67***	0.087
Delano	15	118.60*	0.818
Dinuba	15	97.69*	0.406
Exeter	22	47.74*	0.468
Firebaugh	14	174.40*	1.000
Fresno	19	124.99*	1.000
Hanford	21	65.15*	0.449
Kerman	6	109.44*	1.000
Madera	16	124.46*	1.000
Mendota	15	101.50*	0.446
Reedley	17	171.14*	1.000
Sanger	16	43.88*	0.410
Shafter	15	120.61*	1.000

Notes: *** indicates statistical significance at the 10% level, ** indicates significance at the 2.5% level, and * indicates significance at the 0.5% level. All figures are reported in constant 1982–84 dollars.

Model

- Demand:

$$D = \exp\left[\delta_0 + \delta_1 P + \delta_2 Inc + \delta_3 R + \delta_4 S + \epsilon^d\right]$$

where P is price, Inc is income, R is rainfall, and S is a proxy for population. Note: infinite marginal utility as $D \to 0$, and zero marginal utility at finite level of consumption.

- Extraction costs:

$$C = h^{\alpha_1} D^{\alpha_2} \exp\left[\alpha_0 + \epsilon^c + \xi\right]$$

where h is aquifer height,

  - ϵ^c is measurement error (not obervable to regulator)
  - ξ is a cost shock observable to the regulator, but not to the econometrician

Dynamics

- Aquifer height is the endogenous state variable, which evolves as follows:

$$h_{t+1} = \gamma_1 h_t + \gamma_2 D_t + \gamma_3 R_t + \epsilon_t^h$$

Regulator behavior

- The regulator has weighted welfare function:

$$\pi\left(P,\xi\right)\equiv E\left[\nu CS\left(P,\epsilon^{d}\right)-\left(1-\nu\right)TR\left(P,\epsilon^{d},\epsilon^{c},\xi\right)\right]$$

- where CS is consumer surplus:

$$CS\left(P,\epsilon^{d}\right)\equiv\int_{P}^{\infty}D\left(\epsilon^{d},p\right)dp$$

- and TR is net revenues:

$$TR\left(P,\epsilon^{d},\epsilon^{c},\xi\right)\equiv P\cdot D\left(\epsilon^{d},P\right)-C\left(D\left(\epsilon^{d},P\right),\epsilon^{c},\xi\right)$$

- The regulator is assumed to maximize

$$E\left[\sum_{\tau=1}^{\infty}\beta^{\tau}\pi_{t+\tau}\right]$$

Estimation I

- The equations for demand, costs, and aquifer height are estimated in a first stage:

$$
\begin{aligned}
\ln(D_{it}) &= \delta_0 + \delta_1 P_{it} + \delta_2 Inc_{it} + \delta_3 R_{it} + \delta_4 S_{it} + \epsilon^d_{it} \\
\ln(C_{it}) &= \alpha_1 \ln(h_{it}) + \alpha_2 \ln(D_{it}) + \xi_{it} + \epsilon^c_{it} \\
h_{i,t+1} &= \gamma_1 h_{it} + \gamma_2 D_{it} + \gamma_3 R_{it} + \epsilon^h_{it}
\end{aligned}
$$

- Note: in the second equation, ξ_{it} and D_{it} may be correlated, so we can't just use OLS
- Evolution of R and S also estimated in a first stage.

Estimation II

- Estimation of the remaining parameters (including the welfare weight ν and the variance of ξ) is done using a nested fixed point algorithm.
- This involves solving the dynamic problem for each candidate parameter. Outer loop is maximum likelihood.

TABLE IV

FIRST-STAGE PARAMETER ESTIMATES[a]
(A = DEMAND, B = LIFT-HEIGHT LAW OF MOTION,
C = PUMPING COSTS, D = NONPUMPING COSTS)

Variable		Coefficient	Standard Error
A:	Constant	7.27	0.17
	Price	7.49×10^{-3}	2.97×10^{-3}
	Virtual Income	4.03×10^{-5}	9.74×10^{-6}
	Rainfall	1.20×10^{-4}	5.37×10^{-5}
	Connections	1.70×10^{-4}	1.43×10^{-5}
B:	Lift-Height (−1)	0.97	1.32×10^{-2}
	Constant	0.80	2.55
	Extraction	6.35×10^{-4}	2.05×10^{-4}
	Artificial Recharge	4.73×10^{-4}	2.28×10^{-4}
	Rainfall (−1)	0.01	1.03×10^{-3}
	AVG	0.77	0.18
C:	Constant	−1.66	0.89
	Lift-Height	1.09	0.18
	Extraction	1.18	7.08×10^{-2}
D:	c_0	80.02	6.21
	c_{Clovis}	−15.37	11.60
	c_{Dinuba}	110.83	22.75
	c_{Exeter}	−32.24	9.06
	$c_{Firebaugh}$	24.19	13.88
	c_{Kerman}	−17.59	12.45
	c_{Madera}	−18.58	7.73
	$c_{Mendota}$	58.75	25.36
	c_{Sanger}	−14.73	10.75
	$c_{Shafter}$	−27.00	16.20

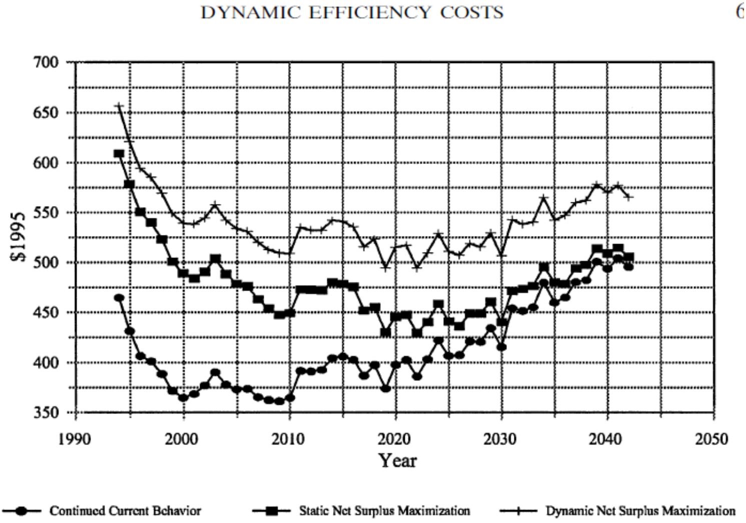
TABLE V

NESTED FIXED-POINT ESTIMATION ALGORITHM PARAMETER ESTIMATES $\beta = 0.95$, $n = 116$, LOG-LIKELIHOOD $= -2209.16$

Parameter	Estimate	Standard Error
υ	0.73	5.44×10^{-3}
ρ_0	−20.00	24.33
ρ_1	0.58	0.23
σ_ξ	135.00	28.46

Results and Counterfactuals

- Timmins find that each dollar of net taxes spent subsidizing water results in 0.45 of consumer surplus.
- He considers three possible paths:
  - Business as usual
  - Static surplus maximization ($\nu = .5$, $\beta = 0$)
  - Dynamic surplus maximization (($\nu = .5$, $\beta = .95$)


DYNAMIC EFFICIENCY COSTS
6
700
650
600
550
500
450
400
350
$1995
1990
2000
2010
2020
2030
2040
2050
Year
Continued Current Behavior
Static Net Surplus Maximization
Dynamic Net Surplus Maximization

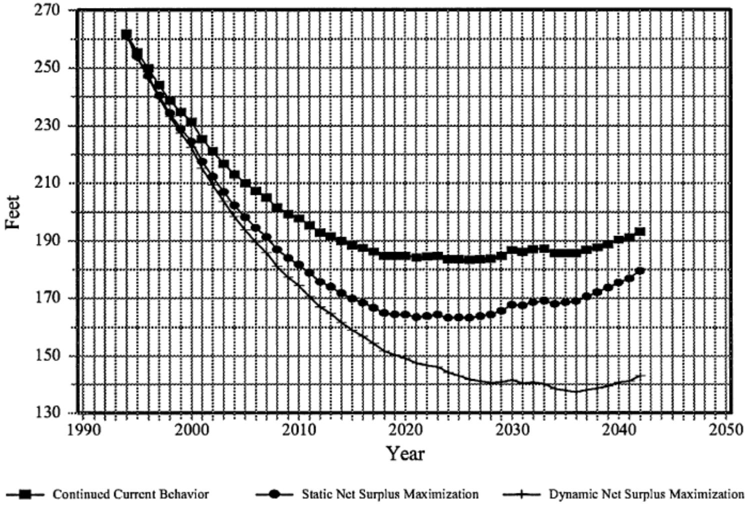


FIGURE 4.—Predicted lift-heights.

"Estimating Dynamic Models of Imperfect Competition"
Bajari, Benkard, and Levin (2012)

Overview

- A simulation-based approach to estimating dynamic games; essentially the same as Hotz, Miller, Sanders, and Smith (1994)
- A two-step approach
  1. Estimate *what* firms do – estimate policy functions
  2. Explain *why* they do it – find parameters that rationalize policies as best responses

Model

- Firms $i = 1, \ldots, N$
- State variable $s_t \in S$
- Actions $a_{it} \in A_i$
- Private i.i.d. payoff shocks ν_{it} with known distribution G
- Per-period payoff function$\pi_i\left(a_{it}, s_t, \nu_{it}; \theta\right)$
- State transition process $P\left(s_{t+1} | s_t, a_t\right)$
- Firms maximize expected discounted profits:

$$E\left[\sum_{\tau=t}^{\infty} \pi\left(a_{i\tau}, s_\tau, \nu_{i\tau}; \theta\right) | s_t\right]$$

Model: Ryan (2012)

- Application to understand impact of regulation of cement industry
- Actions include a quantity decision (Cournot game), capacity investments, entry, and exit
- State variable is the capacities of active firms.

First stage

- Estimate policy function $\sigma_i(s, \nu)$
- Estimate state transition process $P(s_{t+1}|s_t, a_t)$
- Both can be done non-parametrically
- We directly estimate $\sigma_i(s, \nu)$ as a probability, not as a function of the idiosyncratic error ν. Typically, strategies will follow a cutoff rule in ν, and given a distributional assumption on ν, we can back out the cutoffs from the probabilities.
- Multiplicity ignored. Using data from just a single market, no equilibrium selection is needed. Using data from multiple markets, we need to assume that they are all in the same MPE.

Forward simulation

Value function given strategy profile:

$$V_i(s_t, \sigma; \theta) = E\left[\sum_{\tau=t}^{\infty} \pi_i(\sigma_i(s_\tau, \nu_{i\tau}), s_\tau, \nu_{i\tau}; \theta) | s_t\right]$$

Simulation allows us to approximate the expectation over this sum. Our estimate of V will be an average over a large number of simulations S with a large number of periods T approximating the infinite sum.

1. Start at a given state $s_0 = s$, draw private shocks from distribution G
2. Calculate the action $a_{i0} = \sigma_i(s_0, \nu_{i0})$ for each agent i
3. Draw a new state s_1 using transition probabilities $P(s_1 | s_0, a_0)$
4. Repeat steps 1-3 for large number of periods T (or until each player reaches a terminal state)

Linearity

- Having a linear profit function,

$$\pi_i\left(a, s, \nu_i; \theta\right) = \Psi\left(a, s, \nu_i\right) \cdot \theta$$

simplifies the computational burden of forward simulation dramatically

- Ultimately, we want to compute value functions based on the simulations. Linearity allows us to write:

$$V_i\left(s_t, \sigma; \theta\right) = E\left[\sum_{\tau=t}^{\infty} \pi_i\left(\sigma_i\left(s_\tau, \nu_{i\tau}\right), s_\tau, \nu_{i\tau}\right) \cdot \theta | s_t\right] = W_i\left(s_t, \sigma\right) \cdot \theta$$

- In this case, we only need the simulation to calculate W, and then we can just multiply W by θ in order to evaluate V for different parameters.

Estimation

- $V_i(s, \hat{\sigma}_i, \hat{\sigma}_{-i}; \theta)$ is the estimated value function for the estimated strategy profile (which should be approximately the true equilibrium strategy profile).
- $V_i(s, \widetilde{\sigma}_i, \hat{\sigma}_{-i}; \theta)$ is the estimated value function for a deviation from the equilibrium strategy:
- Main idea behind BBL's estimator: we want

$$V_i(s, \hat{\sigma}_i, \hat{\sigma}_{-i}; \theta) \geq V_i(s, \widetilde{\sigma}_i, \hat{\sigma}_{-i}; \theta)$$

  for all $\widetilde{\sigma}_i$

Estimator

- Differences:

$$g(x;\theta) = V_i(s, \hat{\sigma}_i, \hat{\sigma}_{-i}; \theta) - V_i(s, \widetilde{\sigma}_i, \hat{\sigma}_{-i}; \theta)$$

  where x denotes a combination of i, s, and $\widetilde{\sigma}_i$.

- Objective function:

$$Q(\theta) = \sum_{x \in X} (\min\{g(x;\theta), 0\})^2$$

  where X is some large set of possible deviations

- $\hat{\theta} = \min_\theta Q(\theta)$

Results: Ryan (2012)

- Ryan allows fixed costs, entry costs, scrap values, and equilibrium behavior to differ before and after regulations were implemented in 1990.
- He has data from 1980-1999, which isn't a lot given the richness of the state space. What allows him to estimate the model is having many regional markets (assumed to all share the same MPE)
- Main findings: regulation increases entry costs, leading to greater concentration

"Market-Based Emissions Regulation and Industry Dynamics"
Meredith Fowlie, Mar Reguant, and Stephen Ryan (2014)

Cement

- Cement production is a major GHG contributor (5% of global emissions), and a (moderate) tax of $40/ton of carbon would double variable costs of production.
- Motivation: regulation could lead to changes market power, and leakage may limit the effectiveness of regulation imposed within a single market.

Model

- Model is much like Ryan (2012), but augmented with a model of imports:

$$\begin{aligned} \text{Local demand:} \quad \ln Q_m &= \alpha_{0m} + \alpha_1 \ln P_m \\ \text{Import supply:} \quad \ln M_m &= \rho_0 + \rho_1 \ln P_m \end{aligned}$$

- They ignore several potential mitigation methods (switching to new technologies and potentially switching fuel sources) because such switches are not observed in the data. However, entrants will enter with state-of-the art technology.

Counterfactuals

- They consider different policy designs: emissions permit auctioning, grandfathering, dynamic allocation updating, and a border tax adjustment
- For each policy regime, they compute the optimal carbon price, given an assumed social cost of carbon.

Table 9: Optimal carbon prices for different mechanisms

	Federal τ_f^*	Coastal τ_c^*	Inland τ_i^*	Welfare Δ at τ_f^*	Welfare Δ at $\{\tau_c^*, \tau_i^*\}$	Welfare Δ at $\tau = \text{SCC}$
SCC = \$ 20						
Auctioning	0	0	0	0	0	-14,886
Grandfather	0	0	0	0	0	-6,609
Output	0	0	0	0	0	-2,519
BTA	0	0	0	0	0	-6,141
SCC = \$ 45						
Auctioning	5	5	15	905	1,316	-12,890
Grandfather	10	5	35	1,357	2,259	-5,839
Output	25	15	60	1,047	1,628	619
BTA	20	25	15	5,991	6,269	3,150

Notes: Carbon prices in \$. Welfare in M\$. Optimal carbon prices computed on a grid including {0, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65}.

Figure 5: Abatement Curves

(a) Abatement Average Cost (leakage ignored) (b) Abatement Average Cost (leakage-corrected)