MODELING HETEROGENEITY IN RESPONSE TO WATER POLICIES: A FIXED EFFECTS, FINITE MIXTURE APPROACH

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Overview: Understanding Effectiveness of Utility Demand Side Management Programs

- Trillions of dollars in water infrastructure investments will be needed in the near future… much of which is demand driven. (Western Governors Association, 2011)

- An alternative the supply development: demand-side management (DSM) programs

    - DSM savings not currently built into planning forecasts.

- Need to understand who is reducing, how much they are reducing, and how reductions change over time.

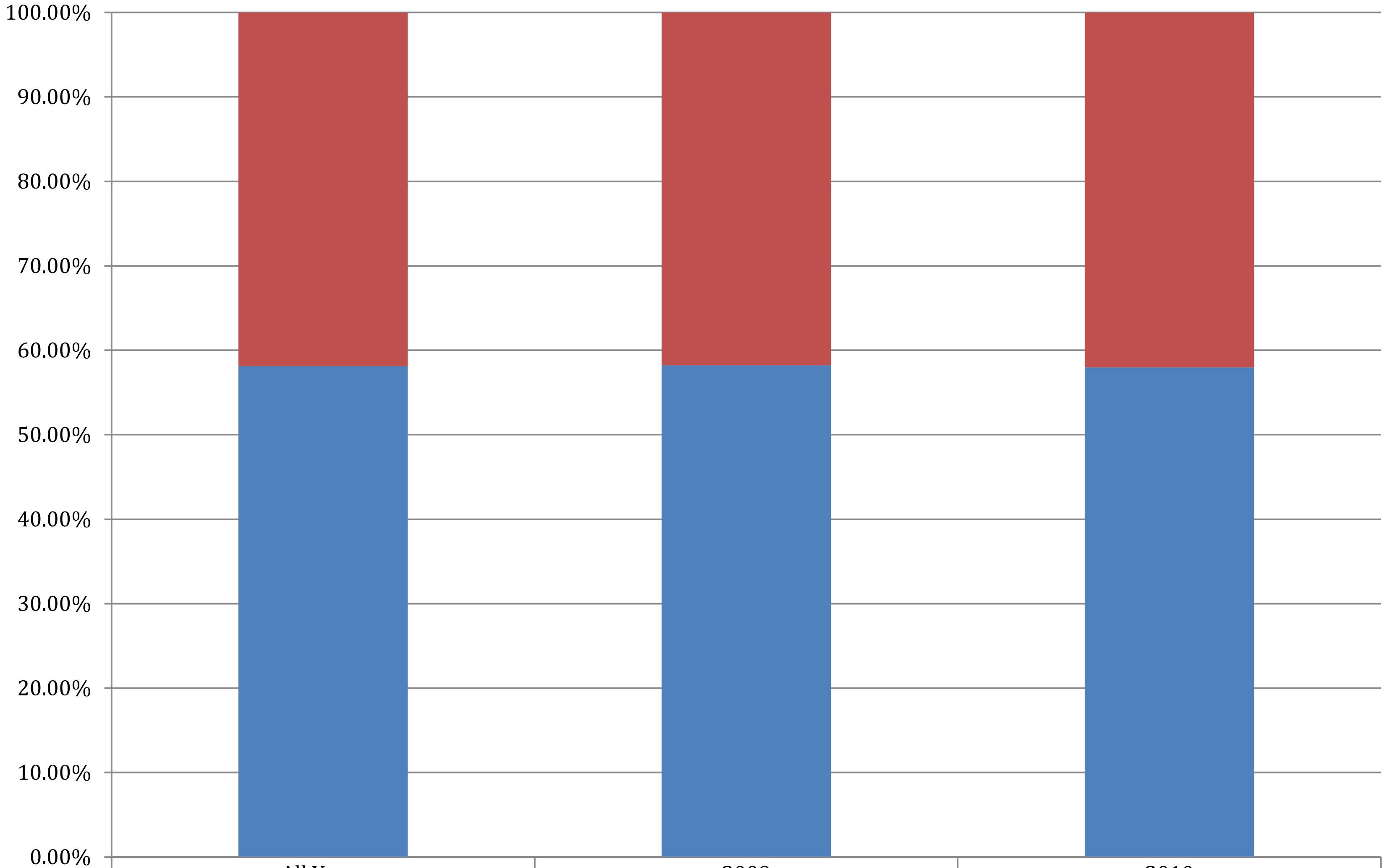
    - Equity
    - Future effectiveness of DSM programs
    - Accurate demand modeling

Overview: Understanding Effectiveness of Utility Demand Side Management Programs

- Challenges & Sources of Heterogeneity:
  - Utility policies complex and confusing to the consumer.
  - Ex: Price
    - Complex rate structures (IBR)
    - Lag between use and receipt of bill
    - Consumption depends upon infrastructure

    - Can expect heterogeneity in consumers' decision making processes across households and across time.
      - Which price?
      - Infrastructure
      - Demographic variables

Which Best Explains the Rate Structure the Utility Currently Uses (Correct v. Incorrect)



	All Years	2009	2010
Incorrect	41.86%	41.75%	42.00%
Correct	58.14%	58.25%	58.00%

Overview: Traditional Approaches to Heterogeneity

Assume data have a shared distribution:

$$f(w; x, \beta)$$

- Include dummy variables or interaction terms for believed to cause heterogeneity.
- If using panel data, use fixed or random effects.
- E.g.: (Grafton et al, 2011)

- Problem with this approach:
  - Assumes marginal effect of included variables is the same for all users.
  - Fixed effects assumes omitted variables are constant over time.
  - We need to know how decision process varies across individuals and parameterize model accordingly.

Overview: Traditional Approaches to Heterogeneity

Assume subsets of data come from different distributions:

- Estimate separate demand functions for distinct user groups

$$f_j(w_j; x_j, \beta_j) \qquad\qquad f_k(w_k; x_k, \beta_k)$$

E.g.: Kenney, et al (2008)

Problem with running models for subsets of users:

- Researcher defined groups may not reflect true heterogeneity in the data.
  - Biased coefficients.
  - Inaccurate demand forecasting.

Overview: Finite Mixture Approach to Heterogeneity

Assumes total distribution of the data is actually a discrete mixture of distributions.

- “Latent Class” Model
- Useful when we don’t have demographic data or know the nature of the heterogeneity.
- Find unique coefficients for latent classes.

$$f(w) = \sum_{j=1}^{k} \pi_j \, f_j(w; x, \beta_j)$$

Previous Applications:

- Health care demand (Deb and Trivedi, 2002)
- Energy loads (Sing, Pal, and Labor, 2010)
- Choice experiments (Boxall and Adamowicz, 2002).

- FMM can be used to capture heterogeneity when the nature of that heterogeneity is unknown.

Application of FMM: Water Demand

- Urdiales, et al (2013): find 5 latent classes corresponding to varying levels of policy responsiveness.
  - Don't use fixed effects.
    - Omitted variable bias.
  - Limited panel
    - Treat data as a cross-section.

Our research:

- Identify heterogeneity across individuals and across time.
- Apply a fixed effects, finite mixture model (Deb and Trivedi, 2013).

- Examine how heterogeneity changes across individuals **and across time** in response to a policy shock—i.e., if we don't believe $\boldsymbol{\pi_j}$ is constant across all bill periods.

$$f(y) = \sum_{j=1}^{k} \boldsymbol{\pi_j} f_j(y; x, \beta_j)$$

Estimation: Background

- 2002: Record low precipitation for large Colorado water provider.
- July 2002: Utility uses water restrictions, seasonal block-rate pricing, price increases, rebates, and education programs to decrease water demand.
  - “**Drought Period”**
- **2006-2010:** Block rates become permanent; prices increases and education programs continue.
  - Watering restrictions are lifted.
  - Price increases are larger than those during the drought.
  - **“Post-drought period”**

Research Questions

1) Can we identify latent classes corresponding to varying levels of policy responsiveness?

- Short term changes in demand resulting from policy shocks.

2) How do the latent classes evolve over time?

- Does use of short-term policies lead to long-term changes in demand ("demand hardening")?
  - Behavioral change
  - Changes in infrastructure

3) Does the FMM capture heterogeneity better than single distribution and split-sample models?

- Welfare implications

Estimation: Data and Approach

Step 1A: Estimate Fixed Effects FMM for 2001-2005 (“Drought Period”)

Step 1B: Post estimation:

- Classify billing periods
- Identify individuals who had high-policy response billing periods.

Step 2A: Estimate coefficients for latent classes for “Post-drought” period (2006-2010).

Step 2B: Post estimation:

- Classify billing periods.
- Determine if high responders in shock period were also high responders in price-only period.

Estimation: Data and Approach

- Data:
  - 365,711 household water use records from 1998-2010
    - 140 billing periods for 2,612households
  - Policy data
    - Watering restrictions
    - Price increases
    - Use of block-rate pricing structure
  - Weather data
    - Temperature
    - Precipitation

Estimation: Data and Approach

- Log-log model using (lagged) average price

$$lnw = \beta_0 + \beta_1 \, Price + \beta_2 Rperdays + \beta_4 Totprecip + \beta_5 Maxtemp + \beta_6 \, Bpdays + \varepsilon$$

- Fixed effects to control for omitted individual-level variables (Deb and Trivedi, 2013)

- Instrument for average price using individual consumption block prices

- Use only summer months (June, July, and August)

Estimation Results: Latent Classes vs. OLS and Split Sample Models (Drought Period)

	OLS	OLS: Split sample (High relative Users)	OLS: Split sample (Low relative Users)		FMM: Class 1 Responders	FMM: Class 2 Responders
Price	-0.42*** (0.011)	-0.40*** (0.023)	-0.42*** (0.018)		-0.292*** (0.011)	-1.167*** (0.071)
Class Shares:					85.6%	14.4%

*** indicates α=0.01

Low relative outdoor water use: Summer use<=2 x Winter Use
Med. Relative outdoor water use: Summer Use=2-3 x Winter Use
High Relative outdoor water use: Summer Use >3 x Winter Use

Estimation Step 2 Results: Latent Classes vs. OLS and Split Sample Models

(Post-drought period)

	OLS	**OLS: Split sample (High relative Users)**	**OLS: Split sample (Low relative Users)**		**FMM: Class 1 Responders**	**FMM: Class 2 Responders**
Price	-0.30*** (0.006)	-0.31*** (0.013)	-0.27*** (0.009)		-0.29*** (0.005)	-0.38*** (0.045)
Class Shares					90%	10%

*** indicates α=0.01

Estimation Results:

How does class membership evolve over time?

"High Response" Households in Drought and Post-Drought Periods

	Drought (-1.16)	Post-drought (-0.38)
High-response households	39.98%	22.06%
Only 33.3% of "high responders" in shock period are also high responders in price-only period.		

Estimation Results:

How does class membership evolve over time?

Logit model for probability a household is a high responder in drought and post-drought periods, as a function of pre-drought water use

	Drought high responder	**Post-drought high responder**
High relative outdoor	0.267*** (0.012)	0.519*** (0.015)
Low relative outdoor	0.253*** (0.010)	-0.114*** (0.014)

Key Results:

1)Can we identify latent classes corresponding to varying levels of policy responsiveness?

- “Baseline” price elasticity in drought and post-drought periods, of -0.3
- Higher responsiveness after consumers receive (or actually look at) a high bill?
  - Large decreases in demand from a small subset of households/billing periods.

2) How do the latent classes evolve over time?

- All consumers are less responsive to prices in the post-drought, despite the steeper price increases that occurred from 2006-2010.
- 67% of high responders drop out of high response class after 2006.

Key Results:

3) Does the FMM capture heterogeneity better than models than single distribution models and split-sample models?

- Single distribution OLS model gives only "average" price elasticity.
  - May under or over-estimate price elasticities for some users/billing periods.
  - Doesn't reflect fact that lower average elasticity post-drought results from high outdoor users' decreased responsiveness.

- Split-sample models may fail to capture true heterogeneity in the data.
  - Households may have similar policy responsiveness even if we wouldn't think to group them together.

Questions?

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