Industrial Reorganization: Learning about Patient Substitution Patterns from Natural Experiments

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"Industrial Disorganization"

Many new empirical industrial organization studies forecast counterfactual outcomes [...], without a clear foundation in experience. [...] We'd expect such a judgment to be based on evidence showing that the simulation-based approach delivers reasonably accurate predictions.
–Angrist and Pinske (JEP 2010)

Discrete Choice Demand - A Shaky Foundation?

- Cornerstone of empirical IO
- Models based on **untestable** assumptions
  - IIA
  - Limited differentiation among products
- Little exogenous variation in choice sets

Natural Disasters Randomly Change Choice Set

- Hospitals destroyed/closed by natural disasters
- Internal Validity: Areas immediately surrounding relatively unaffected
- External Validity: Disasters in range of environments

Hospitals Good Industry to Examine Demand Models

- Hospitals are important
  - Hospital care more than 5 percent of GDP
  - Hospital demand models used to address a variety of questions
- Rich patient-level data helpful for identification
- Several critiques
  - Brennan and Guerin-Calvert, 2013; Doane, Froeb, and Van Horn, 2012; May, 2013

Experimental Validation in Other Settings

- Vending Machines: Conlon and Mortimer (2013)
- School Choice: Pathak and Shi (2014)
- Schooling and Fertility: Todd and Wolpin (2006)

What you should take away from this talk

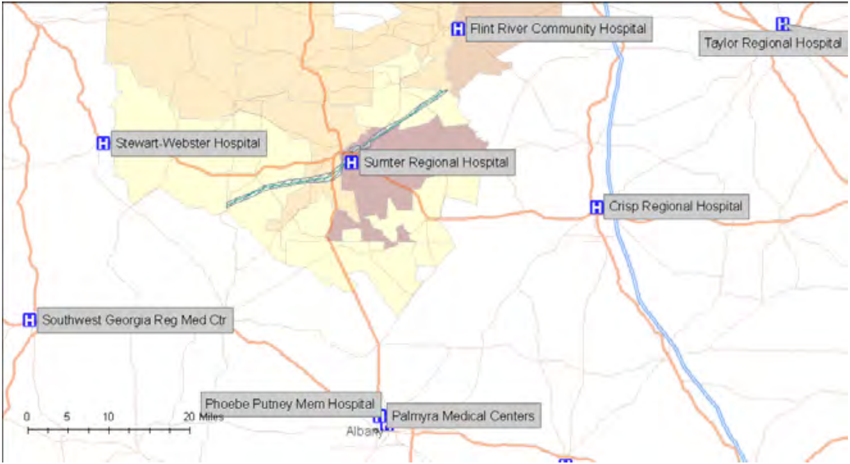
- Heterogeneity in unobserved hospital quality is important
- We provide guidance on which models to use
  - Use combination of semiparametric and parametric models
- Widely used models lead to different policy conclusions
  - Model choice matters

Overview

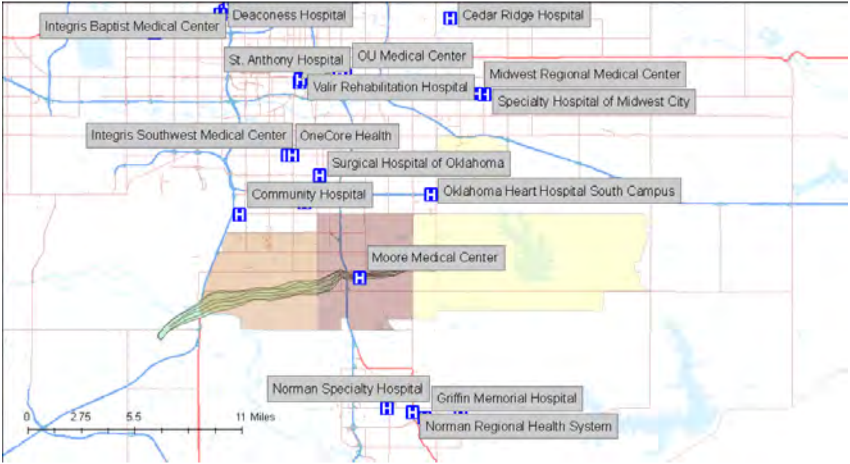
Natural Disasters

Location	Month/Year	Severe Weather	Hospital(s) Closed
Northridge, CA	Jan-94	Earthquake	St. John's Hospital
Americus, GA	Mar-07	Tornado	Sumter Regional Hospital
New York, NY	Oct-12	Superstorm Sandy	NYU Langone
			Bellevue Hospital Center
			Coney Island Hospital
Moore, OK	May-13	Tornado	Moore Medical Center

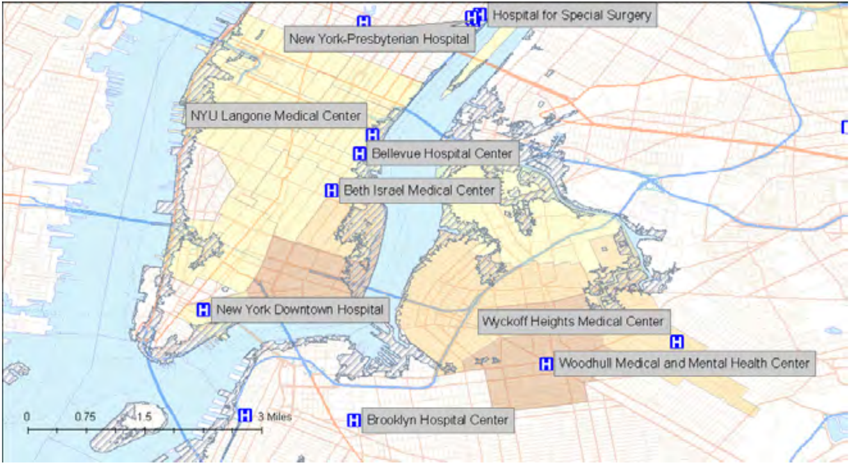
Tornado: Americus, GA



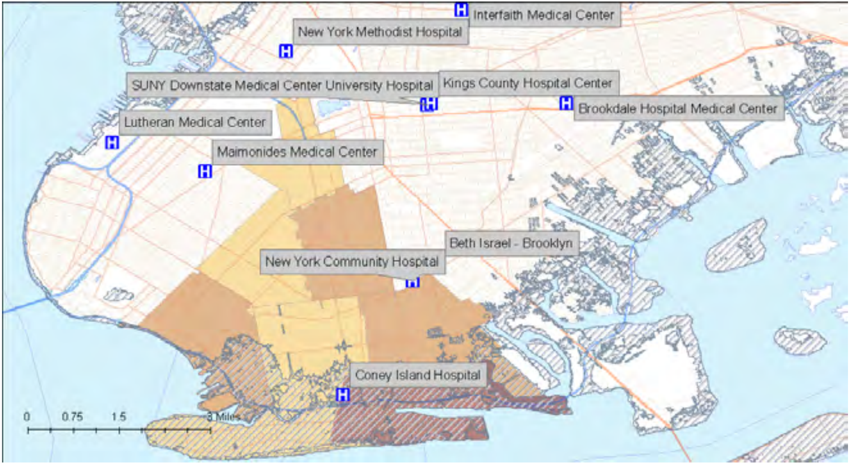
Tornado: Moore, OK



Superstorm Sandy: Manhattan, NY



Superstorm Sandy: Brooklyn, NY



Earthquake: Los Angeles, CA

Primitives

Hospitals $j = 0, 1, ..., J$, where 0 indexes the outside option.

Patients $i = 1, ..., N$

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- Patient's choice of hospital is denoted h_i
- Patients choose hospital one time

Focus is Prediction and Welfare

Probability of choosing j

$$Pr(h_{it} = j) = \frac{\exp(\delta_{ij})}{\sum_{k \in S} \exp(\delta_{ik})}$$

WTP for hospital j

$$WTP_i^j(S) = \log\left(\sum_{k \in S} \exp(\delta_{ik})\right) - \log\left(\sum_{k \in S/j} \exp(\delta_{ik})\right)$$

We examine wide set of models used in literature

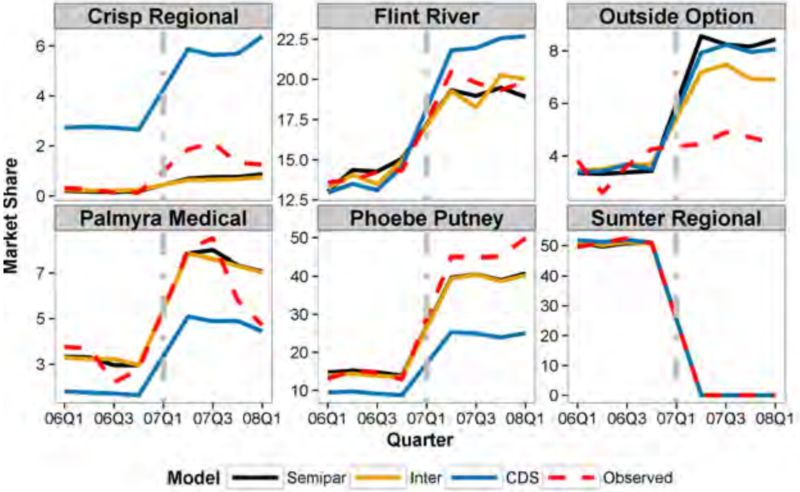
Name	**Travel Time**	**Hosp Characteristics**	**Hosp Indicators**
Indic	×	×	✓
Char (**Garmon WP**)	✓✓	✓✓	×
CDS (**RAND '03**)	✓✓	✓✓✓	×
Time (**May WP**)	✓	×	✓
Ho (**JAE '06**)	✓	✓✓✓	✓
GNT (**AER '15**)	✓✓	✓✓	✓✓
Inter	✓✓✓	×	✓✓✓
Semipar (**Raval, Rosenbaum, Tenn WP**)	Hosp Indicators Interacted with Bins		

Experimental Design

- Estimate models on period before disaster
- Examine performance on period after disaster
  - Out of sample in two dimensions
- Drop all admissions and discharges in month of disaster

Some Models Match Market Shares Well

Sumter

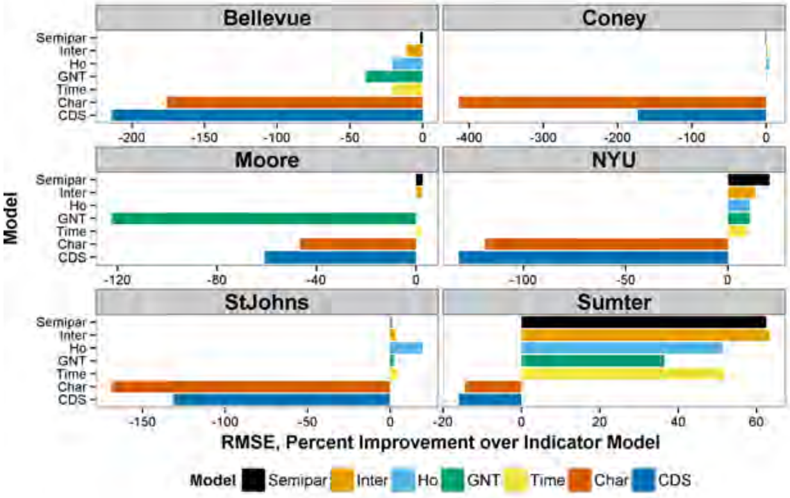


Examine Relative Model Performance

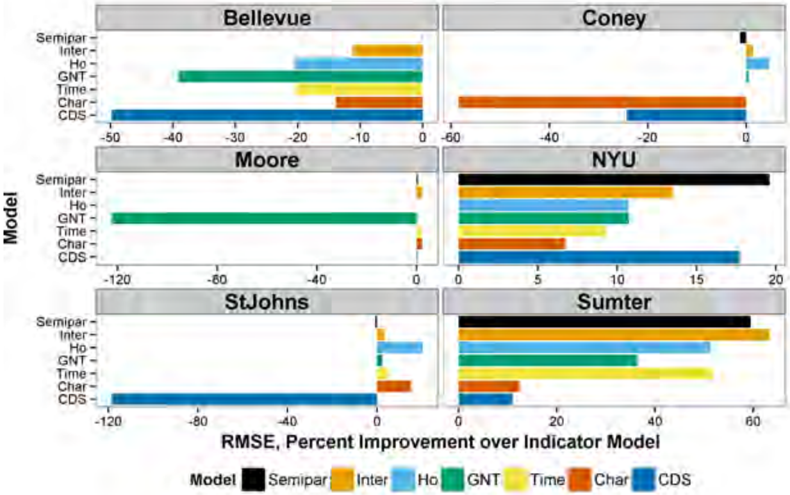
- Examine Percent Improvement in RMSE over Indicator Model
  - $-1 * (\frac{RMSE_{Model}}{RMSE_{Indic}} - 1)$

- Three Sets of Predictions:
  - Aggregate Shares
  - Aggregate Diversion Ratios: $\frac{y_{j,1} - y_{j,0}}{y_{dest,0}}$
  - Individual Predictions

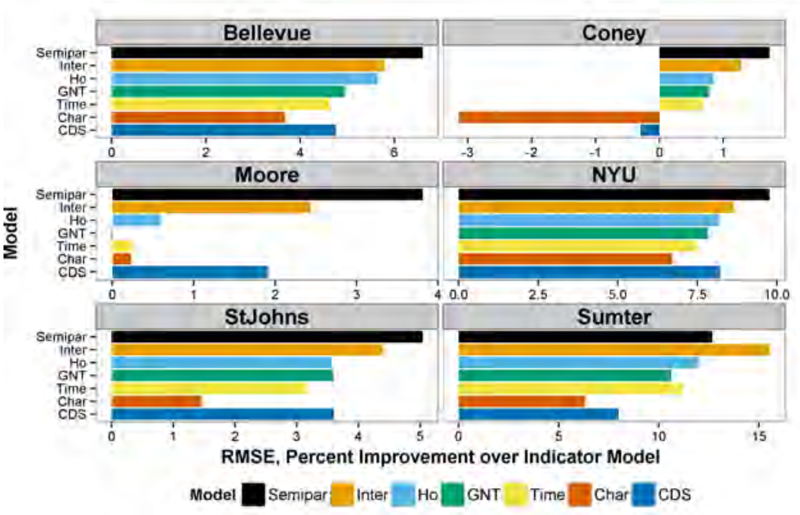
Comparing Models: Aggregate Shares



Comparing Models: Aggregate Diversion Ratio



Comparing Models: Individual Predictions



Optimal Model Combination

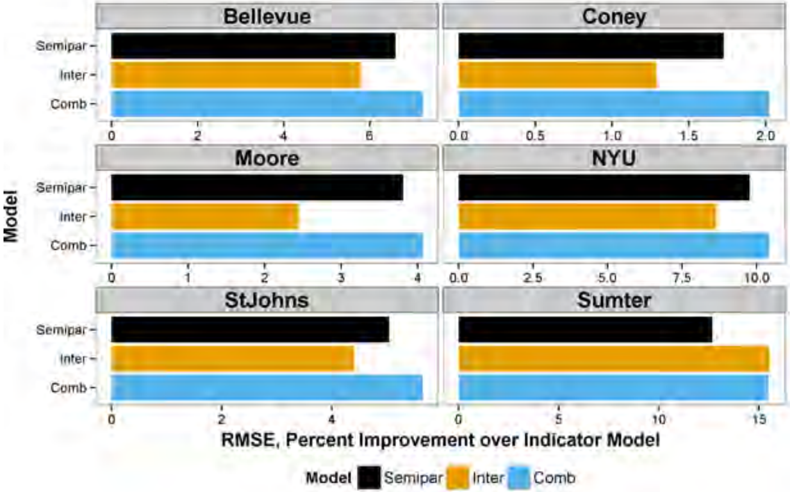
$$y_{ij} = \beta^{Semipar}\hat{y}_{ij}^{Semipar} + ... + \beta^{CDS}\hat{y}_{ij}^{CDS} + \epsilon$$

- Weights non-negative, sum to one (Timmerman (2006))
- Averaged across experiments

Model	Weight
Semipar	51%
CDS	26%
Inter	16%
Ho	7%

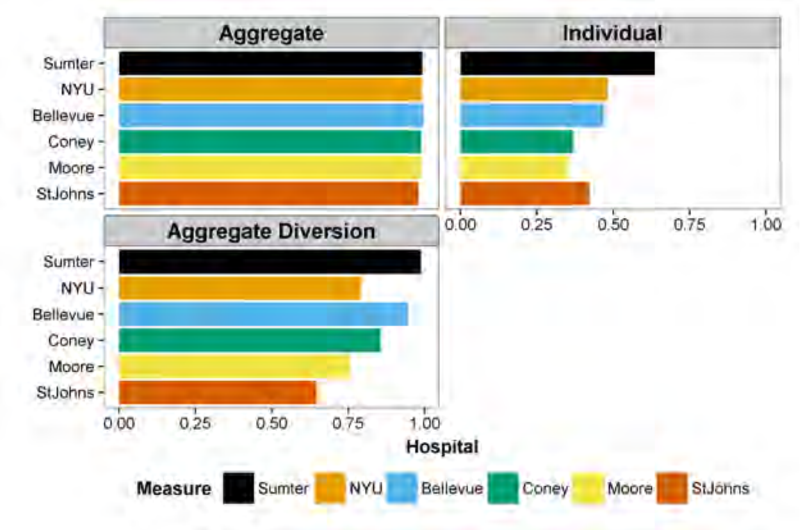
Comparing Models: Individual Predictions

Model Combination



How Well Do Discrete Choice Models Perform?

Correlation Coefficient



Robustness

- Changing Choice Set Patients
- Capacity Constraints
- Case Mix
- Medicare Insurance Only
- Removing Destroyed Areas
- Doctors

Counterfactual Hospital Mergers

- Hospitals with higher WTP have higher market power
  - Suppose hospital k and l are merging
  - Change in WTP

$$WTP_{(k,l)}(S) - WTP_k(S) - WTP_l(S)$$

approximates change in market power from merger

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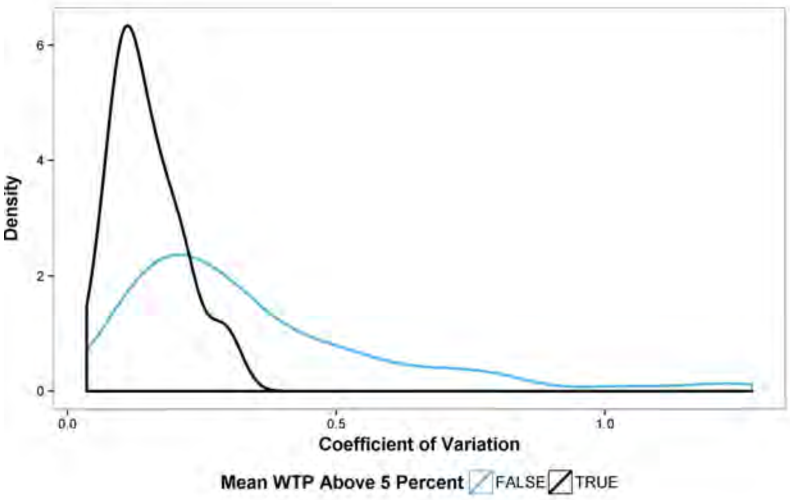
- We examine all possible counterfactual mergers (95 in total)

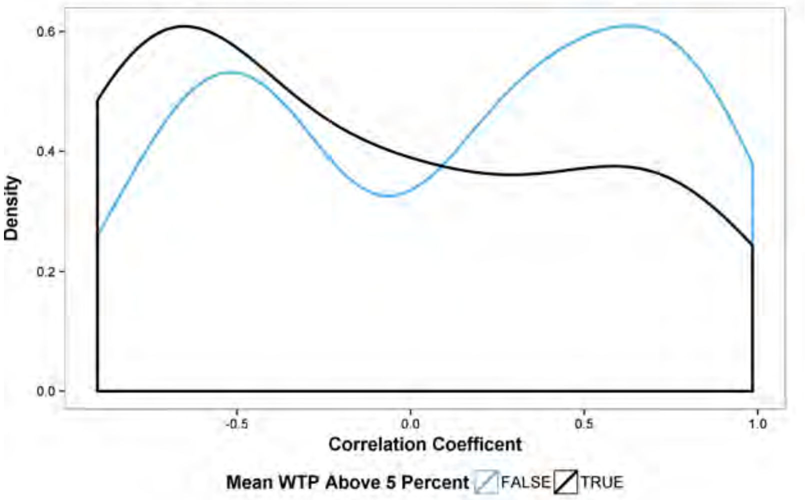
Meaningful Predicted Welfare Differences Across Models

SD / Mean



Meaningful Predicted Welfare Differences Across Models

Correlation, RMSE and Percent Change in WTP



Conclusion

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Future Work: Examining Machine Learning Models