The Regional Economic Effects of Airport Infrastructure and Commercial Air Service

Quasi-Experimental Evaluation of the Economic Effects of Commercial Air Service Near Smaller Airports

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Motivation

- Policymakers, business leaders, media, and public commonly believe airports are critical to connecting a region to the national and international economy
- Small commercial airports are heavily subsidized
  - Airport Improvement Program
  - Essential Air Service
  - FAA, etc.

Previous Research

- Many economic impact studies utilizing input-output models
  - Essentially cheerleading
  - Always see a positive impact
- Econometric models
  - Usually analyze only larger airports
  - Often assumed that smaller airports do not affect economy in the same way as larger airports

Research Question

- Does the presence of commercial air service positively affect the economy of the surrounding region?
  - Treatment is simply *presence*
  - Estimation methods and models impose a minimal number of assumptions
    - Let the data speak
  - Subsequent research looks at more complex treatments

Outline

- Data
- Construction of control groups
  - Quasi-experimental policy evaluation
- Spatial bootstrap methods
  - Produce more accurate measurement of uncertainty of estimates
- Model
- Results

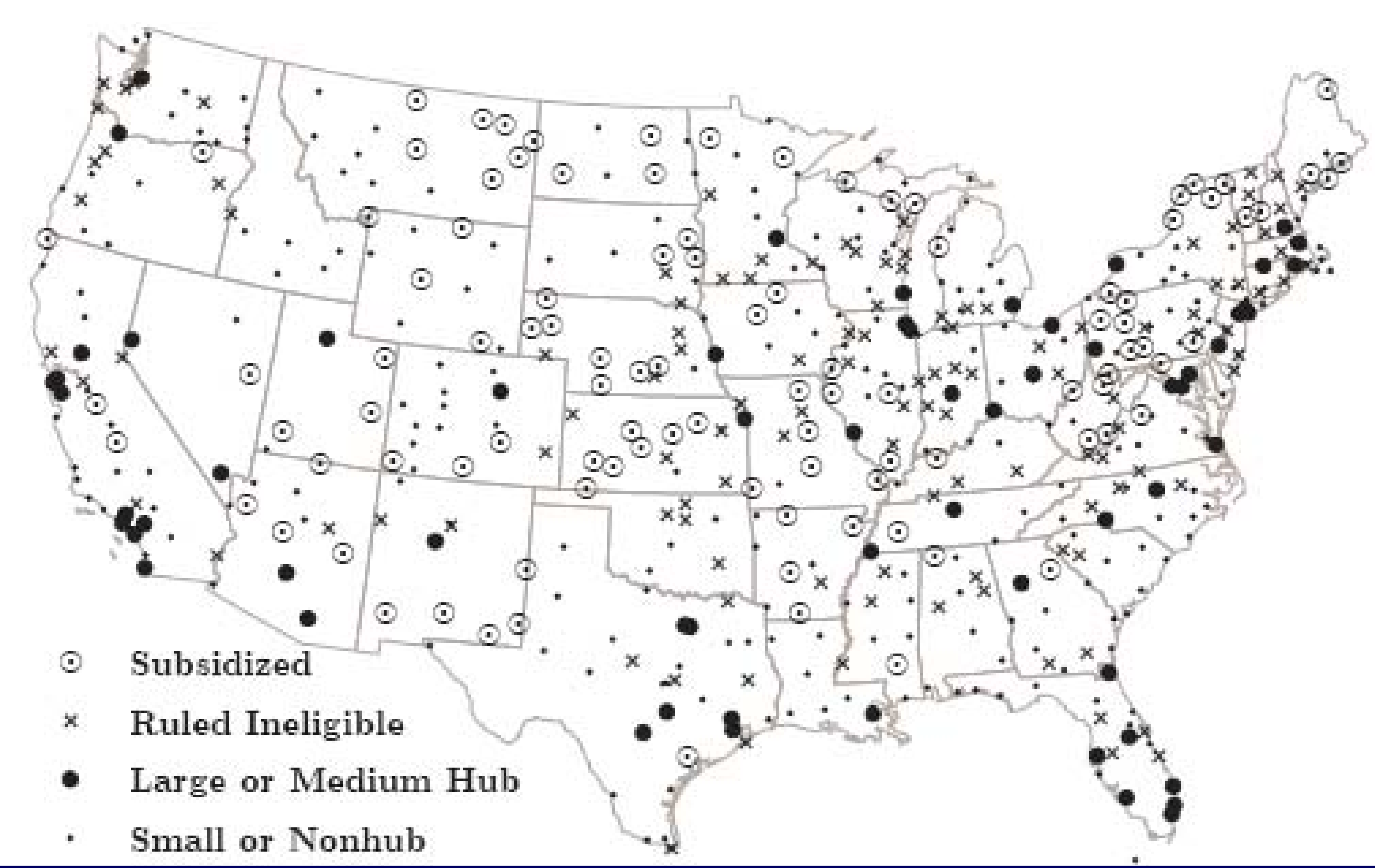
Data

- Post-deregulation, 1980 to 2004
- *Terminal Area Forecast* data
  - Airports with 500+ enplanements in a year designated as having commercial service
    - Level chosen in order to eliminate airports with occasional charter but include airports receiving EAS subsidies
- Other data
  - CBP, REIS, Census

Data

- Treatment defined three ways:
  - Commercial service within county
  - Commercial service within 40 miles of county centroid
  - Commercial service within 70 miles of county centroid
- Three groups of counties
  - Counties that always had commercial service
  - Counties that never had commercial service
  - Counties with a mixture of commercial service

Data



Subsidized
Ruled Ineligible
Large or Medium Hub
Small or Nonhub

Control Groups

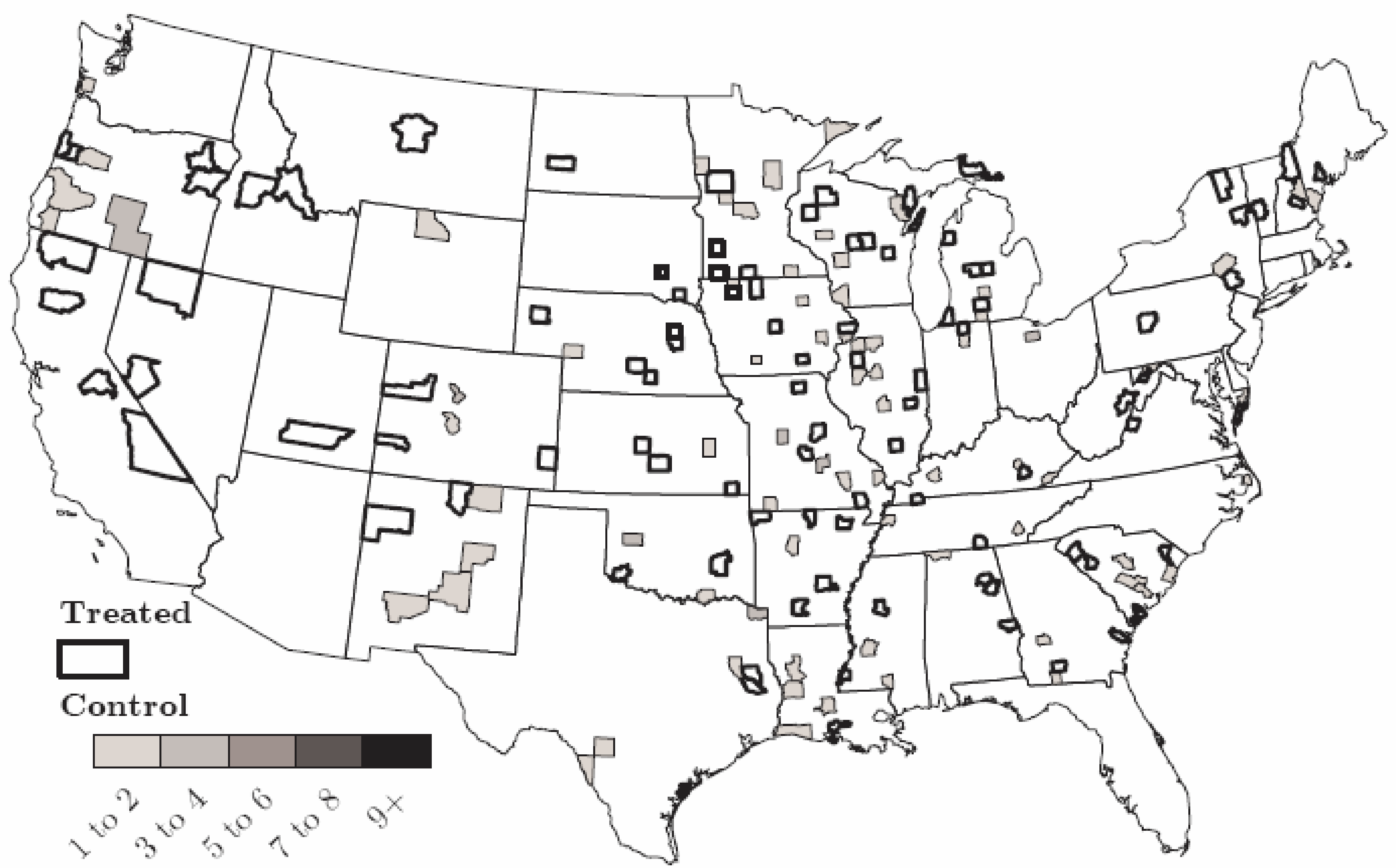
- Quasi-experimental method that selects a comparable set of treated and control counties
- Attempts to balance variables of the two groups
  - Should reduce or eliminate problems due to endogeneity of the treatment
  - Reduces model dependence

Control Group Construction

- Genetic matching algorithm (Sekhon 2007, Diamond and Sekhon 2005)
  - Modified to be computationally feasible for a large set of matching variables
- Ex: Results when service is within county:

	Unmatched		*Matched*			
			No CBP		*With CBP*	
	Tr	*Ctr*	*Tr*	*Ctr*	*Tr*	*Ctr*
Always	130	256	113	56	79	36
Never	130	1,677	105	83	98	74

Ex: Never Controls (no CBP)



Spatial Bootstrap Methods

- Many studies with multiple time periods report standard errors that are too low
  - Do not account for serial autocorrelation in error term (Bertrand et al. 2004)
  - Do not account for spatial error autocorrelation
- Bootstrap methods account for these problems by sampling from the data
- Block bootstrap samples all years for a county together

Spatial Residual Method

- Based on Anselin (1990)
  - Modified to account for time (block bootstrap) and for control groups
- Used for spatial lag models
- Samples residuals from counties
  - Modifies all dependent variables using a spatial transformation of the residuals based upon spatial lag

Spatial Residual Method

- Disadvantages:
  - Requires a spatial lag model
  - Assumes residuals distributed independently
    - Hurt by heteroskedacity in errors
    - Cannot use a random effects model

Spatial Window Block Bootstrap

- Modifies spatial window bootstrap for time and control groups
- Samples “windows” of counties that are close together to form a new dataset
  - Estimates model using these new datasets
- Not favored due theoretical considerations (edge effects)
  - Monte Carlo simulation shows it performs best

Model

- Reduced form of a Carlino-Mills type model:

$$
\begin{aligned}
P_{i,t} &= h^{P}_{i,t}(\Psi'_{i,t}, \Omega_{i,t} \mid \Omega_i) \\
E_{i,t} &= h^{E}_{i,t}(\Psi'_{i,t}, \Omega_{i,t} \mid \Omega_i) \\
I_{i,t} &= h^{I}_{i,t}(\Psi'_{i,t}, \Omega_{i,t} \mid \Omega_i) \\
D_{i,t} &= h^{D}_{i,t}(\Psi'_{i,t}, \Omega_{i,t} \mid \Omega_i)
\end{aligned}
$$

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Model

- Integrated with difference in differences model

$$\ln y_{i,t}^{j} = \alpha + \alpha_1 d_t + \alpha^1 d^j + \beta d_t d^j + z_{i,t}^{j} \delta + \epsilon_{i,t}^{j}$$

Model

- Integrated with a mixed effects model

$$
\begin{aligned}
\ln P_{i,t} &= \beta^P SERV_{i,t} + \lambda^P \ln(WP_t) + X_i\delta^P + \alpha_t(P) + \alpha^i(P) + \epsilon^P_{i,j} \\
\ln E_{i,t} &= \beta^E SERV_{i,t} + \lambda^E \ln(WE_t) + X_i\delta^E + \alpha_t(E) + \alpha^i(E) + \epsilon^E_{i,j} \\
\ln I_{i,t} &= \beta^I SERV_{i,t} + \lambda^I \ln(WI_t) + X_i\delta^I + \alpha_t(I) + \alpha^i(I) + \epsilon^I_{i,j} \\
\ln D_{i,t} &= \beta^D SERV_{i,t} + \lambda^D \ln(WD_t) + X_i\delta^D + \alpha_t(D) + \alpha^i(D) + \epsilon^D_{i,j}
\end{aligned}
$$

Model

- Nonparametric:

$$
\begin{aligned}
\ln P_{i,t} &= \beta^P SERV_{i,t} + \alpha_t(P) + \alpha^i(P) + \epsilon^P_{i,t} \\
\ln E_{i,t} &= \beta^E SERV_{i,t} + \alpha_t(E) + \alpha^i(E) + \epsilon^E_{i,t} \\
\ln I_{i,t} &= \beta^I SERV_{i,t} + \alpha_t(I) + \alpha^i(I) + \epsilon^I_{i,t} \\
\ln D_{i,t} &= \beta^D SERV_{i,t} + \alpha_t(D) + \alpha^i(D) + \epsilon^D_{i,t}
\end{aligned}
$$

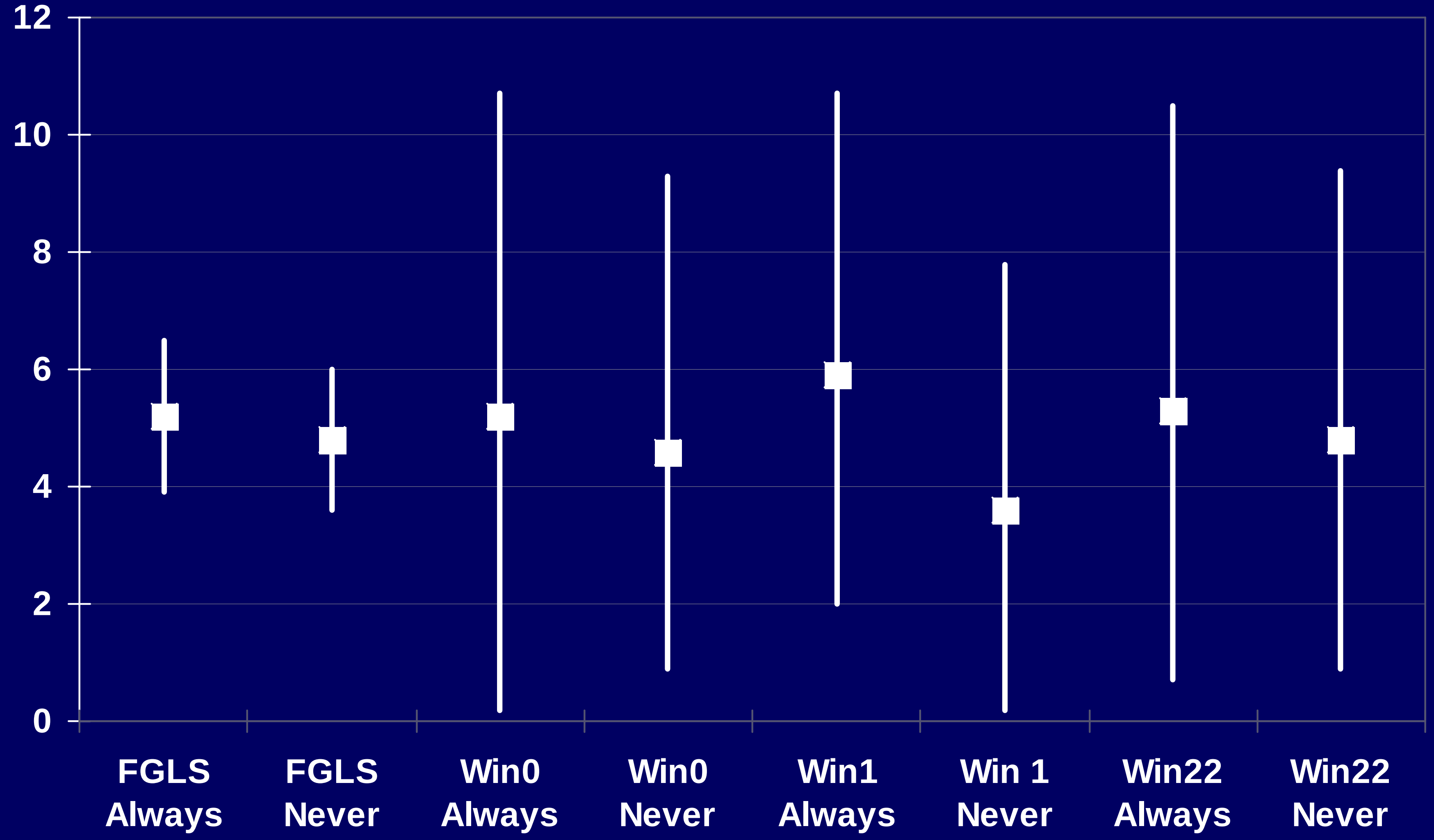
Results

- For commercial service inside the county, the median treatment effect is consistent across variables, parametric vs. nonparametric, and control groups
  - Generally around 5%
- Difficulties with the residual block bootstrap
  - Due to small estimate of λ, no random effects
  - Small λ likely due to insufficient instruments

Results

- Estimates of spatial window block bootstrap are dependent upon the window being used
  - e.g. Counties with first order 70 mile weights matrix vs. transposed nearest 22 counties
  - First order matrix will give biased result if the treatment effect is different over space – over-samples some regions
  - Important: Estimated treatment effect is just an average of the treatment effect in the treated counties

Results: Inc, Nonparametric,CBP



Results: 40, 70 Miles

- Treatment effects decrease in size
  - Not as statistically significant
  - Some negative in 70 miles
- Bigger differences between block bootstrap and spatial window block bootstrap
  - Treated counties are in clusters, so spatial blocks sample more of them at once

Future Research

- Examining how the treatment effect differs across counties
  - Ex: Is economic effect stronger with more enplanements (Yes)
- Possible identification problem in current research
  - Could economic effects come from general aviation benefiting from infrastructure improvements?
    - Future results suggest this could be true