Discussion of Teardowns and Demolitions in Chicago… by Daniel McMillen

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Key Points of Paper

- Specifies a reduced form model for demolitions, and notes that the parameters of this model vary considerably across the Chicago region
- Uses Conditionally Parametric Probit model to estimate the heterogeneity of the reduced form parameters across the sample.
- Loosely interprets differences as due to different prevalence of “teardowns” versus “demolitions”

Strengths of Methodology

- Avoids model misspecification by making the fewest assumptions required to identify model.
- Maps are a nice way to organize the huge output from the estimation procedure and to visualize the heterogeneity.

Weaknesses

- Conditional parametric models are hard to estimate and frequently are inefficient relative to standard parametric approaches.
- Results may be sensitive to “bandwidth” choices.
- Standard errors are downward biased since they condition on chosen “bandwidth.”
- Difficult to formally compare with standard parametric approaches.

Forecasting

- Presumably the main use of this model would be to forecast future demolitions.
- One way to compare against other models would be a holdout sample –
  - leave the last 2 – 3 years out of the estimation sample.
  - Forecast the number of demolitions for each census tract and each model (might be hard to get confidence bands for these forecasts).

Alternative Latent Class Model

- The theory and literature suggest two distinct types of demolitions
  - 1. Buildings being torn down to make room for new buildings (“teardowns”)
  - 2. Buildings being torn down to create vacant land (“demolitions”)
- Suggests a latent class model with 2 classes

$$P_i = \text{Prob}\left[\text{Parcel}_i \text{ in teardown class}\right] * \text{Prob}\left[\text{Parcel}_i \text{ demolished} \mid \text{class } t\right]$$
$$+ \text{Prob}\left[\text{Parcel}_i \text{ in demolition class}\right] * \text{Prob}\left[\text{Parcel}_i \text{ demolished} \mid \text{class } d\right]$$
$$= \Phi\left(\alpha z_i\right) * \Phi\left(\beta_t x_i\right) + \left(1 - \Phi\left(\alpha z_i\right)\right) * \Phi\left(\beta_d x_i\right)$$

Estimate model by Maximum Likelihood:

$$\max_{\alpha,\beta} \sum_{i=1}^{N} y_i \ln\left[\Phi\left(\alpha z_i\right) * \Phi\left(\beta_t x_i\right) + \left(1 - \Phi\left(\alpha z_i\right)\right) * \Phi\left(\beta_d x_i\right)\right]$$
$$+ \left(1 - y_i\right) \ln\left[1 - \left(\Phi\left(\alpha z_i\right) * \Phi\left(\beta_t x_i\right) + \left(1 - \Phi\left(\alpha z_i\right)\right) * \Phi\left(\beta_d x_i\right)\right)\right]$$

Note that z should contain local neighborhood characteristics