Measurement and Inference on Cross Section and Spatial Interactions

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1 Outline

- The research question

- Example 1: Diffusion in excess housing demand

- Example 2: Interactions in a monetary policy committee

- Example 3: Convergence and inequality across regions

- Estimation of spatial weights matrix
• Understanding interactions in committees

• Spatial dependence driven by factor structures

• Sampling of spatial units

• Further research
2 The research question

- Substantial cross section and spatial dependence in many applications

- Spatial weights matrix
  - representing spatial dependence
  - notions of geographic/ economic/ socio-cultural distance
  - imperfect measurements and uncertainty about drivers
  - huge implications for spatial dependence models

- Key Question: Can we understand spatial interaction without assuming specific drivers of diffusion?
• Emerging literature: Estimating spatial weights *without* *a priori* notions of distance
  
  – consistent with observed pattern of spatial dependence
  
  – using estimates to identify true drivers of diffusion

• In this presentation
  
  – Review three new methods
  
  – Motivate using examples
  
  – Identify new research questions
3 Example 1: Diffusion in excess housing demand

3.1 Structural economic model

- Prices, Demand and Supply (Wheaton, 1990; Hendershott et al., 2002)
  - Three behavioural relationships:
    1. Rate of change of price = \( f(\text{deviation of vacancy rate from natural vacancy rate, deviation of price from equilibrium price}) \)
       \[ \frac{(V_t - V_{t-1})}{V_{t-1}} = \delta_1 (\nu^* - \nu_{t-1}) + \delta_2 (V^*_t - V_{t-1}). \]
    2. Demand = \( f(\text{Price, Neighbourhood conditions, Market conditions}) \)
       \[ D_t = \lambda_0 X_t^{\lambda_1} V_t^{\lambda_2} Y_t^{\lambda_3}. \]
3. In equilibrium, Demand = Supply times Occupancy rate

\[ D_t \equiv (1 - \nu_t) \cdot S_t. \]

- Price-setting through search and matching
  (Wheaton, 1990; Krainer, 2001; Anglin et al., 2003)

4. Degree-of-overpricing (DOP) = f (Neighbourhood conditions, Market conditions, Demand)

\[ \ln DOP_t \equiv \ln V_t - \ln V_t^L = \alpha_0 + \alpha_1 \cdot X_t + \alpha_2 \cdot \ln Y_t + \alpha_3 \cdot \ln D_t. \]

5. Time on the market (TOM) = f (Market conditions, Degree-of-overpricing, Occupancy rate)

\[ \ln TOM_t = \beta_0 + \beta_1 \cdot \ln Y_t + \beta_2 \cdot \ln DOP_t - \beta_3 \cdot \ln(1 - \nu_t). \]
In logs and first differences – all vars. stationary in temporal dimension

We assume: (a) natural value \((V^*)\) fixed (temporally) in the short run, (b) exogenous supply, neighbourhood conditions and market conditions.

\[
\Delta \ln D_t = \lambda_0 \Delta D_{t-1} - \lambda_1 \Delta X_t - \lambda_2 \Delta \ln V_t + \lambda_3 \Delta \ln Y_t + u_t \tag{1}
\]

\[
\Delta \ln V_t = \gamma_0 + \gamma_1 \Delta \ln D_{t-1} + \gamma_2 \Delta \ln V_{t-1} - \gamma_3 \Delta \ln S_{t-1} + \epsilon_{1t} \tag{2}
\]

\[
\Delta \ln DOP_t = \alpha_1 \Delta X_t + \alpha_2 \Delta \ln Y_t + \alpha_3 \Delta \ln D_t - \alpha_4 \Delta \ln V_t + \epsilon_{3t} \tag{3}
\]

\[
\Delta TOM_t = \beta_1 \Delta \ln Y_t + \beta_2 \Delta \ln DOP_t - \beta_3 \Delta \ln D_t + \beta_4 \Delta \ln S_t + \epsilon_{4t} \tag{4}
\]

Structural equations are identified.
3.2 Spatial diffusion in excess demand

- Stack up demand for all regions into a vector

- Spatial error model with autoregressive errors (SEM-AR)

\[
D_t = Z_t \beta + u_t, \quad t = 1, \ldots, T,
\]
\[
u_t = R.W.u_t + \varepsilon_t
\]
\[
\Rightarrow D_t = Z_t \beta + (I - R.W)^{-1}.\varepsilon_t
\]

\(T\) time periods \((t = 1, \ldots, T)\) and \(K\) regions,

\(W\): an unknown spatial weights matrix \((K \times K)\),

\(R = diag(\rho_1, \rho_2, \ldots, \rho_K)\): diagonal matrix containing spatial autoregression parameters for each region, and

\(\varepsilon_t\): \(K \times 1\) vector of independent but possibly heteroscedastic spatial errors

\[
\Sigma = \mathbb{E}(\varepsilon.\varepsilon') = diag(\sigma_1^2, \sigma_2^2, \ldots, \sigma_K^2).
\]
Arbitrary spatial interaction (diffusion) subject to identification constraint: $(I - R.W)$ nonsingular.

**Objective:** to estimate $W$.

### 3.3 What use are such estimates?

- Suppose housing shocks originate from London

- How do the shocks then propagate through space?
• In other words, which is closer to London – Hertfordshire, Buckinghamshire or Birmingham?

  – Geographic distance: Hertfordshire and Buckinghamshire are closer than Birmingham

  – Sociocultural distance: Birmingham may be closer.

• Bhattacharjee and Jensen-Butler (2005)

  – Spatial spillover from excess housing demand in London higher for the South East (Buckinghamshire) and West Midlands (Birmingham) than East of England (Hertfordshire).

  – Hence, geographic distance useful in some cases (London and the South East), not appropriate for others (London and West Midlands, London and East of England).
4 Example 2: Decision making in committees

- Economics of networks: pattern of connections between individual rational agents shapes their actions and determines their rewards.

- An important example is a monetary policy committee (ECB or Bank of England)
  - Members may hold either partisan views depending on region/constituency or vote strategically.

- Like the previous example
  - Members’ voting behaviour represented by regression model including inflation, output gap and markets
– Deviations from such votes may be explained by cross-member interactions through connections weights (similar to spatial weights)

• Bhattacharjee and Holly (2008):
  – Decision making within the Bank of England’s monetary policy committee (MPC)
  – Personalities of members reflected in heterogeneity in the policy reaction functions
  – In addition, significant interactions among members – either strategic or likemindedness
  – Network architectures offer interesting insights into capacity constraints, transaction costs and incentives.
5 Example 3: Convergence and inequality

- Stable differences in productivity across regions in the EU.

- Explanations: innovative capacity, technology transfer/absorption

- Many possible drivers for each, also potentially institutional features

- In empirical studies
  - Useful to allow for relatively unrestricted technology transfer
  - Further, infer on strength and direction of inter-region diffusion ... ... while being agnostic about the specific drivers of such interaction.
6 Estimation of spatial weights matrix

- Bhattacharjee and Jensen-Butler (2005) consider estimation of a spatial weights matrix

- Spatial error model with spatial autoregressive errors (5).

- Estimation problem is only partially identified, up to an orthogonal transformation of interactions.
  Symmetry of spatial weights matrix valid identifying restrictions.

- Proposed algorithm for estimation, bootstrap for standard errors.
  Easy to use, but symmetry assumption may be too strong
Figure 1: Government Office Regions (GORs) in England and Wales
Figure 2: Topological Map of England and Wales based on spatial weights
7 Understanding interactions in committees

- Bhattacharjee and Holly (2008) develop an alternative GMM based method

- Spatial or interaction weights matrices here are unrestricted ...  
  ... except for the validity of the included instruments and other moment conditions.

- The method assumes a nonempty set of other cross section units, ...  
  ... correlated with the units under consideration, ...  
  ... but may change over time, expand or some units may even drop out.

- Application to MPC voting behaviour suggest asymmetry, incomplete connectivity, and heterogeneity in influence.  
  Further, negative interaction weights point to strategic voting.
Figure 3: Connections weights within the Bank of England’s MPC
8 Spatial dependence driven by factor structures

- The above methodologies are based on an important assumption: **Spatial interactions are structural – not driven by unobserved factors.** *This assumption can sometimes be tenuous!*


- Application to changes in real house prices in the UK, find evidence that
  1. Adjustment to shocks involve both region specific and spatial effects
  2. Shocks to London propagated contemporaneously and spatially to other regions, but they impact on other regions with a delay.
  3. New York house prices have direct but lagged effect on London prices.
9 Sampling of spatial units

- Important both for credible data analyses and effective collection of spatial data by statistical agencies.

- Guard against potential sample selection biases
  - Not very well understood – research potential!

- Methods considered here explicitly account for endogeneity in selection of units.
  - Selection endogenously related to the size and importance of spatial units
  - Therefore, sample selection bias is potentially limited.
  - Nevertheless, these issues need to be quantified and addressed.
Selection models can in turn be used to classify core and periphery.
- Useful for developing appropriate survey designs for spatial data.
- Above methods can identify such units and help effective survey design

(Longitudinal) panel nature of the data need to be preserved.
- Important for addressing unobserved fixed and random effects at the cross section level, ...
... but also for accumulating evidences of spatial interaction and diffusion patterns over time.
- Therefore, very important for research that sampling of the same spatial units is continued over substantial time.
10 Further research

- Estimation of interactions provide useful understanding and insights

- Available methods assume either (a) purely structural interactions, or (b) purely factor driven dependence.
  **Combination of the two an important direction of future research**

- **Study of sampling issues required**
  - Design of spatial surveys
  - Implications (sample selection, endogeneity) for inference
  - Implications of estimated interactions for refining surveys

- **Further applications**: convergence and related issues, and beyond.