Inferring Latent Preferences from Network Data

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14 November 2015

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Motivation

very early stages

Methodological

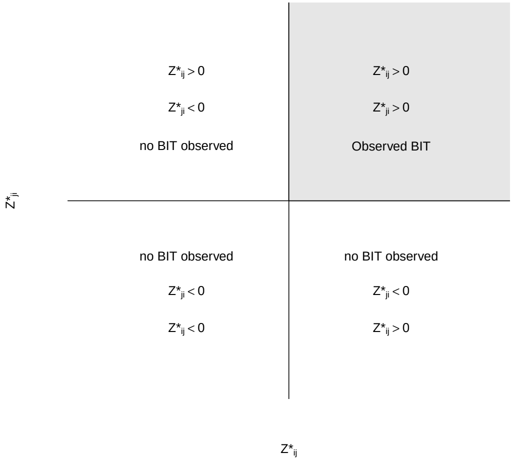
- extend "latent space" models (Hoff et al 2002) to "partial observability" in binary, non-directed graphs
- Build on mixture model approach (Ward et al. 2013)
- Generate improved forecasting and case selection tools

Substantive

- Need convincing model of treaty formation to evaluate effects (Rosendorff & Shin 2012)
- Existing empirical models of BIT formation fail to account for network dependencies
- Observed treaty network and preferences for BITs may evolve dynamically and endogenously
- Identify treaties likely to be breached or to have trouble in ratification

Partial observability

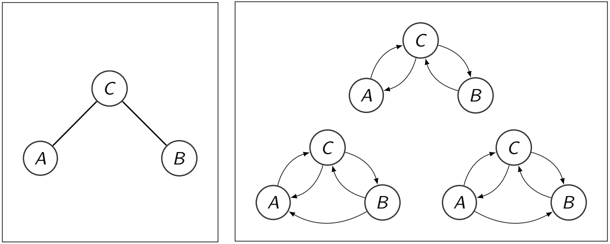
z^*_{ij}: i's net (unobserved) payoff for signing a BIT with j
BIT_{ij} observed iff $z^*_{ij} > 0 \wedge z^*_{ji} > 0$



Observed and latent networks

nondirectional observed network and directional latent relations

Observed network $\mathcal{G}$ **Associated latent networks $\mathcal{G}_1^*, \mathcal{G}_2^*, \mathcal{G}_3^*$**



Random utility & latent variables

$$
\begin{aligned}
z^*_{ij} &= \overbrace{\mu_{ij}}^{\text{systematic}} + \overbrace{\epsilon_{ij}}^{\text{random}} \\
\epsilon_{ij} &= \underbrace{a_i + b_j}_{\text{2nd order dependence}} + \underbrace{u'_i v_j}_{\text{3rd order dependence}} \\
\mu_{ij} &= \beta^{(s)} x^{(s)}_i + \beta^{(r)} x^{(r)}_j + \beta^{(d)} x^{(d)}_{ij} \\
\mu_{ji} &= \beta^{(s)} x^{(s)}_j + \beta^{(r)} x^{(r)}_i + \beta^{(d)} x^{(d)}_{ji} \\
y^*_{ij} &= \begin{cases} 1 & \text{if} \quad z^*_{ij} \geq 0, \\ 0 & \text{otherwise} \end{cases} \\
y_{ij} = y_{ji} &= y^*_{ij} y^*_{ji}
\end{aligned}
$$

Model assumptions & structure

Bayesian model, diffuse priors on hyperparameters, MCMC estimation

$$\begin{pmatrix} z_{ij}^* \\ z_{ji}^* \end{pmatrix} \sim \mathcal{N}_2 \left(\begin{pmatrix} \mu_{ij} + a_i + b_j \\ \mu_{ji} + a_j + b_i \end{pmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right) + \begin{pmatrix} u_i' v_j \\ u_j' v_i \end{pmatrix}, \quad (1)$$

$$\begin{pmatrix} a_i \\ b_i \end{pmatrix} \sim \mathcal{N}_2 \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{bmatrix} \sigma_a^2 & \sigma_{ab} \\ \sigma_{ab} & \sigma_b^2 \end{bmatrix} \right), \quad (2)$$

$$u_i \sim \mathcal{N}_K(0, \sigma_u^2 I), \quad (3)$$

$$v_i \sim \mathcal{N}_K(0, \sigma_v^2 I). \quad (4)$$

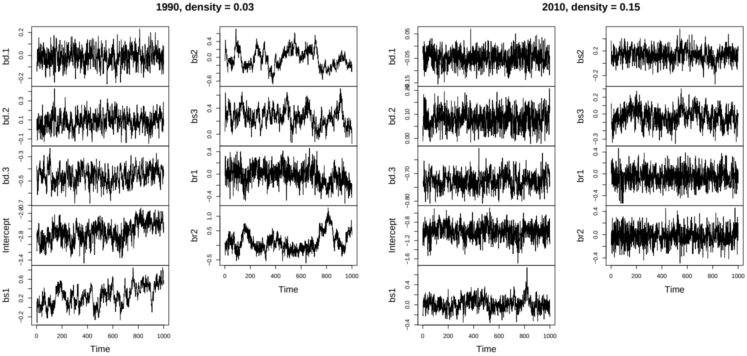
Data

BIT network 1990-2014

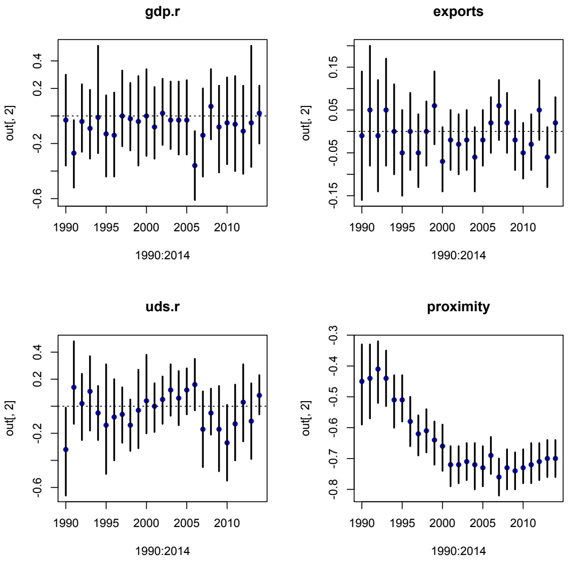
- BIT signing data from UNCTAD
- BITs assumed to remain in place permanently
- Estimated independently for each year
- Covariates: exports, imports, distance, GDP, population, UDS
- One-dimensional latent space assumed.
- Missing covariate data imputed as part of MCMC

Convergence

Convergence problems in sparse networks

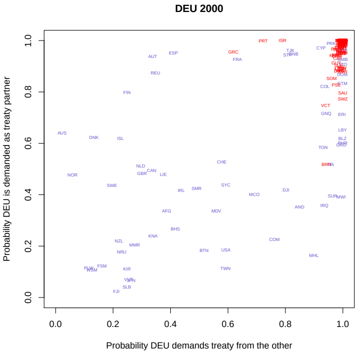


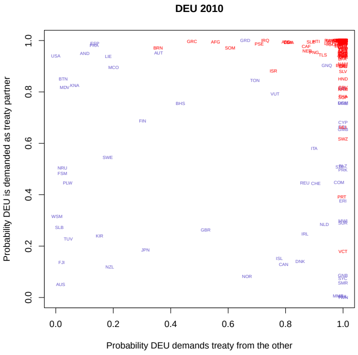
Regression weights over time



Latent preferences and BITs

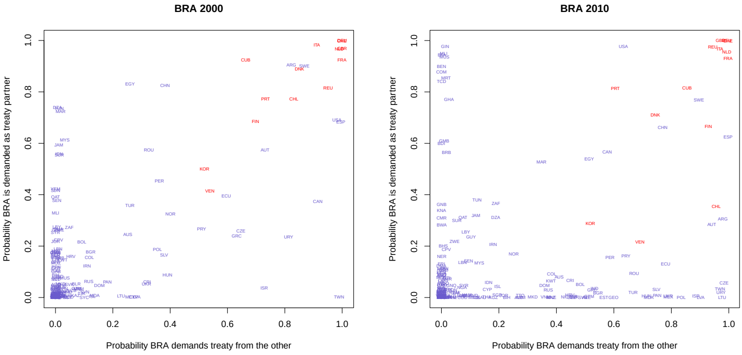
Germany





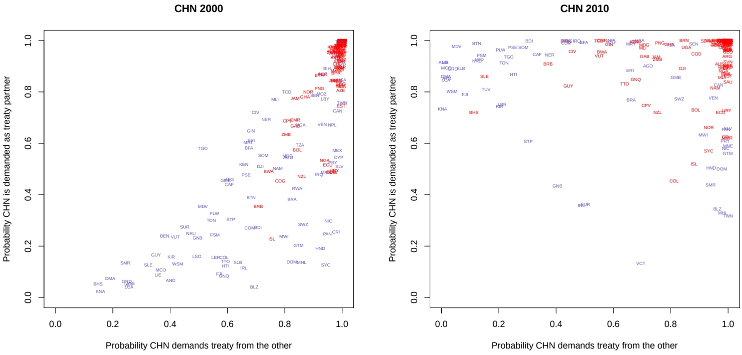
Latent preferences and BITs

Brazil



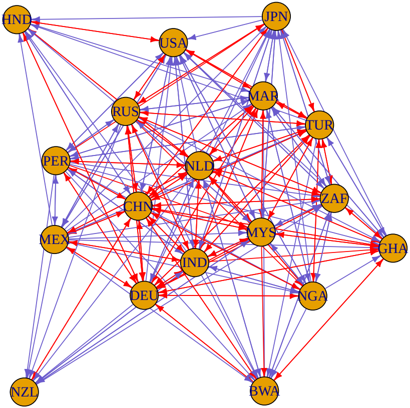
Latent preferences and BITs

China



Examining the predicted network

2014 subset



Conclusion

- Preliminary results suggest benefits in learning about latent preferences
- Even a poorly fitting network model able to recover interesting changes
- Still to do:
  - gather more covariates (US interest rate, transparency)
  - out of sample forecasting comparison
  - dynamic estimation
  - benchmarking against existing models