Modelling area-wide count outcomes with a spatial autoregressive model: An Analysis of Chicago Taxi Trips Data

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Background

- **Spatial Autocorrelation**: the correlation of a variable with itself through space, which violates OLS assumption of independence of observations.

Data & Methods

- Taxi ridership is aggregated by 77 Chicago communities and is analyzed by relating it to three categories of community-level variables.
- A spatial autoregressive model is implemented to account for the spatial dependence of taxi ridership.
- Three different spatial weights are used to test sensitivity, and they are queen-contiguity, rook-contiguity, and distance-based weights.

Global Model

$$log(\boldsymbol{PICKUPS}_i) = \beta_0 + \sum_{j=1}^{5} \beta_j X_{ij} + \beta_6 log(\boldsymbol{COMP})_i + \epsilon_i$$

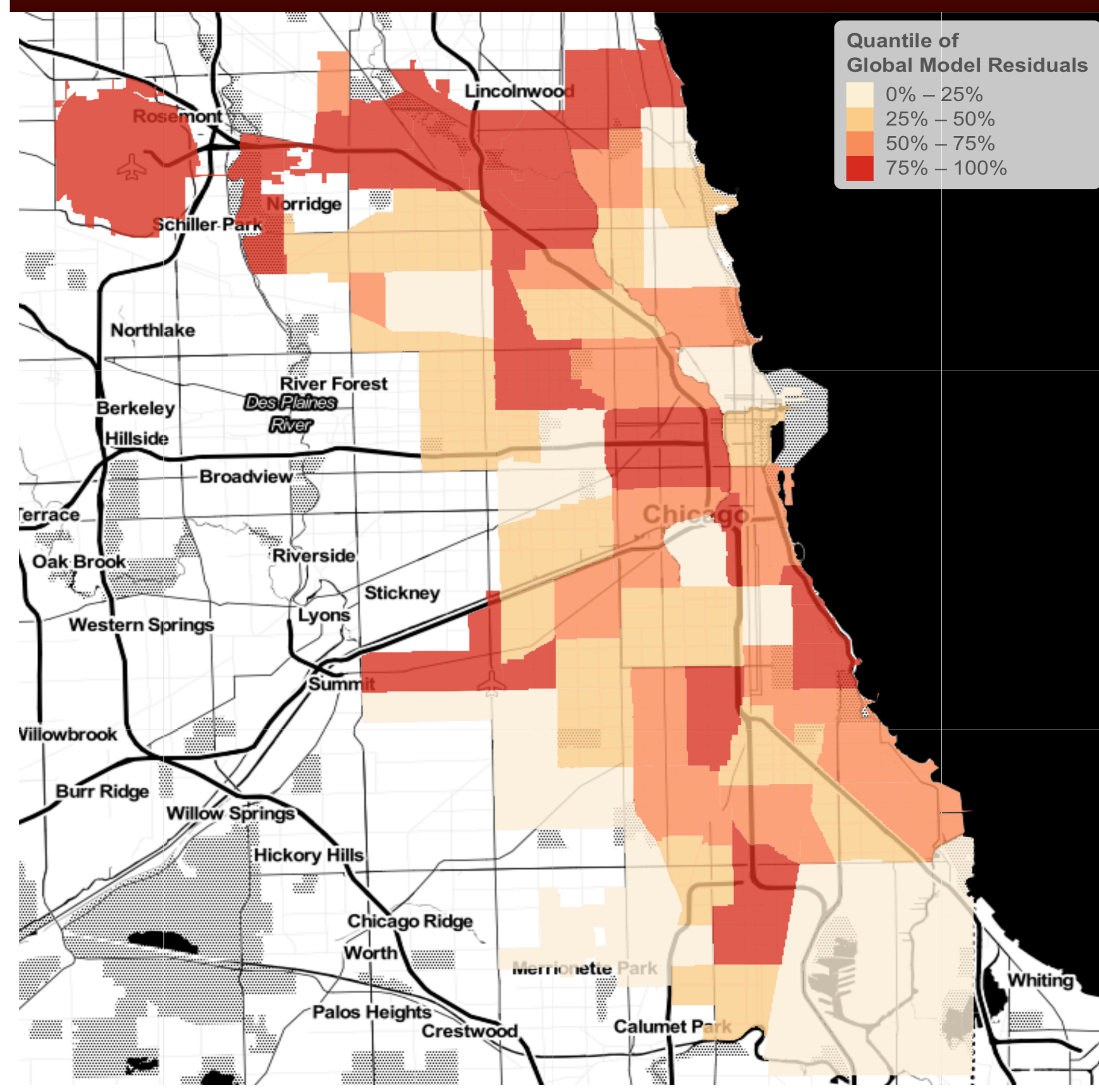
List of Dependent Variables

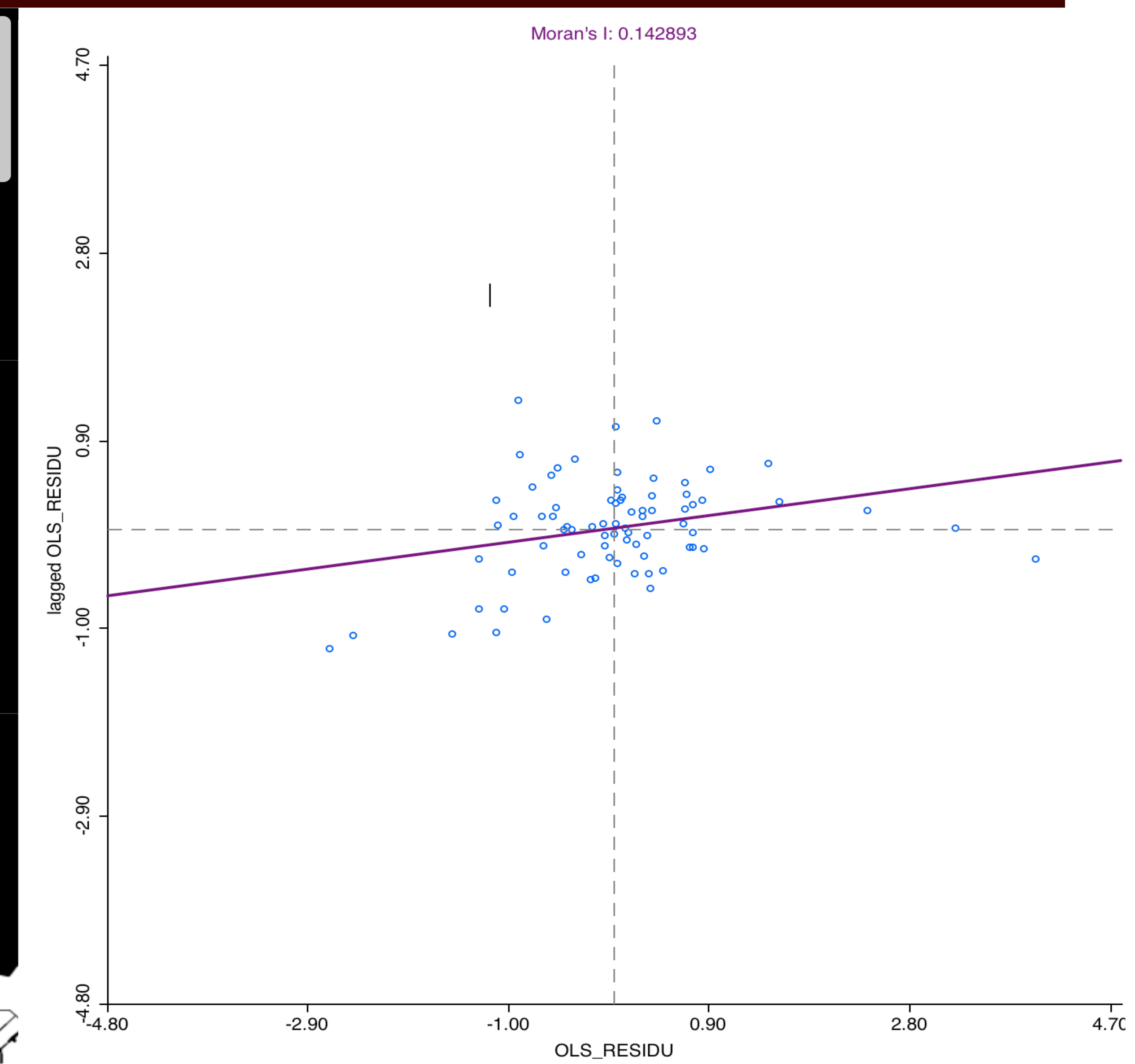
Variable	Definition
PICKUPS	aggregated pickup density

List of Independent Variables

Variable	Definition
Category 1: Socio-demographic	
Variable	Definition
COMMUTER	density of commuters
HARD	the hardship index
Category 2: Built-environment	
Variable	Definition
RESP	% residential land
COMP	% commercial land
Category 3: Urban-transportation	
Variable	Definition
BUSPA	bus stops density
LTRAIND	dummy L'Train stations

Spatial Autocorrelation of Pickups per acre by Moran's I





Lagrange Multiplier Test for Spatial Dependence

Lagrange Description	Test	Queen-contiguity χ^2	Queen-contiguity P-value	Rook-contiguity χ^2	Rook-contiguity P-value	Distance-based χ^2	Distance-based P-value
Spatial Lag	LM_ρ	7.7862	0.00526**	8.1787	0.00424**	7.4904	0.00620**
Robust Spatial Lag	LM_ρ^*	6.4823	0.01090*	5.8552	0.01553*	6.4515	0.01109*
Spatial Error	LM_λ	1.9637	0.16111	2.7183	0.09920	1.2543	0.26274
Robust Spatial Error	LM_λ^*	0.6598	0.41662	0.3948	0.52980	0.2154	0.64260

Note: *p<0.05; **p<0.01

Spatial Autoregressive Model (Lag Model)

$$\boldsymbol{Y} = \rho \boldsymbol{W Y} + \boldsymbol{X \beta} + \boldsymbol{\epsilon}$$

or

$$log(\boldsymbol{PICKUPS}_i) = \rho \boldsymbol{W} log(\boldsymbol{PICKUPS}_i) + \beta_0 + \sum_{j=1}^{5} \beta_j X_{ij} + \beta_6 log(\boldsymbol{PARK})_i + \epsilon_i$$

where ρ is the autoregressive coefficient

$\boldsymbol{W}$ is the spatial weighting matrix

and $\boldsymbol{W}$ $log(\boldsymbol{PICKUPS}_i)$ is the spatially lagged dependent

Results

	Dependent variable: log(TOTALPA) *Global Model (OLS)*	*Spatial Autoregressive (SAR)*
ρ (spatial lag)		0.470*** (0.092)
COMMUTER	0.144*** (0.033)	0.081*** (0.030)
HARD	−0.032*** (0.006)	−0.024*** (0.005)
RESP	−4.821*** (1.218)	−3.307*** (1.051)
log(COMP)	0.498* (0.276)	0.404* (0.227)
BUSPA	21.234*** (6.364)	11.151** (5.414)
LTRAIND	0.982*** (0.348)	0.567* (0.301)
Constant	4.593*** (1.271)	3.423*** (1.075)
R^2	0.82	0.87
σ^2	1.35528	0.914
Akaike Inf. Crit.	248.586	231.576
Residual Std. Error	1.164 (df = 70)	0.956 (df = 69)
F Statistic	53.366*** (df = 6; 70)	

Note: #obs. = 77 for both models *p<0.1; **p<0.05; ***p<0.01

Conclusion

- Global Moran's I and the residuals of global model confirms spatial autocorrelation.
- A spatial autoregressive model greatly outperforms global OLS model in modelling community taxi demand.

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