Spatiotemporal Causal Analysis of Human Mobility on Disease Transmission

Poshan Niraula [1,*], Jorge Mateu [2], Edzer Pebesma [1]

[1] Institute for Geoinformatics, University of Münster, Germany, *pniraula@uni-muenster.de

[2] Universitat Jaume I, Spain

1 INTRODUCTION

- **Goal:** Quantify the causal effect of human mobility changes on COVID-19 transmission.
- **Approach:** Generalized propensity score (GPS) framework with spatial interference using Advan origin–destination mobility networks [2, 1] to estimate direct (δ_1) and spillover (δ_2) effects.
- **Setting:** 177 Modified ZIP Code Tabulation Area (MODZCTA) areas in New York City, March 2020 – July 2022.
- **Challenge:** Time-dependent confounding from behavioral feedback and sensitivity to temporal lags and interference structure.

2 METHODOLOGY

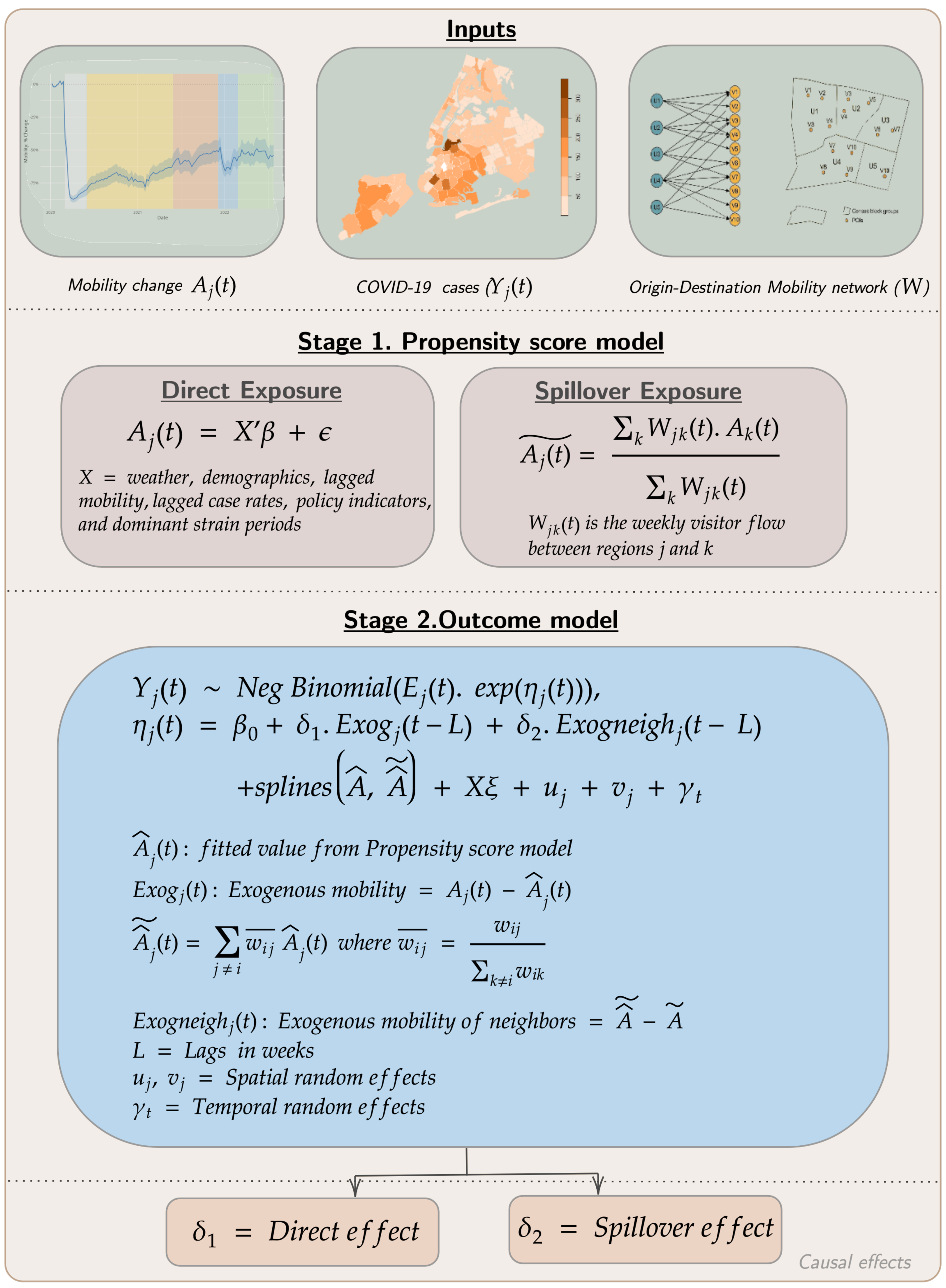

Figure 1: Two-stage spatiotemporal causal inference framework. Stage 1 estimates direct and network-weighted spillover propensity scores. Stage 2 feeds these scores as non-linear adjustments into a negative-binomial outcome model with spatial and temporal random effects, identifying the unconfounded causal effects δ_1 (direct) and δ_2 (spillover).

- **Exposure:** The direct exposure $A_j(t)$ is the weekly percentage change in average foot traffic per point of interest (POI) relative to the pre-pandemic baseline (Jan 6 – Feb 28, 2020) in MODZCTA j. The spillover exposure $\widetilde{A}_j(t)$ is the network-weighted average of neighbouring areas' mobility, constructed from an origin–destination matrix derived from the same Advan data.
- **Propensity score model (Stage 1):** A linear model regresses the direct exposure on local confounders (e.g., socio-demographics, lagged case rates, hospital density). The fitted values define the generalised propensity score (GPS) $(A_j(t), \widetilde{A}_j(t))$ which balances confounders. Residuals from this stage represent the exogenous variation in mobility that is unrelated to the measured confounders.
- **Outcome model (Stage 2):** A negative-binomial mixed model for weekly COVID-19 case counts includes non-linear spline adjustments for the GPS of both the direct and spillover exposures. By conditioning on the GPS, the coefficients on the residualised direct and spillover mobility recover the causal effects δ_1 and δ_2, free of confounding by the measured covariates.

The outcome-model coefficients for δ_1 and δ_2 recover causal effects under the standard assumptions of the GPS framework with interference [2]: **unconfoundedness** (no unmeasured common causes of mobility and COVID-19 cases given the observed confounders), **positivity** (every region could plausibly experience any level of mobility change), **consistency** (observed case counts equal potential outcomes under the realised mobility levels), and **interference structure** (spillover acts solely through the specified mobility network).

3 RESULTS

Table 1: Direct (δ_1) and spillover (δ_2) effects of mobility change on COVID-19 cases. 95% credible intervals shown in brackets; **bold** values indicate significance.

Lag	Model	δ_1 (95% CI)	δ_2 (95% CI)	WAIC
1	Mobility	−0.0097 [−0.1979, 0.1785]	**0.0136** [**0.0073**, **0.0198**]	184651
	Contiguity	−0.0047 [−0.1929, 0.1834]	**0.0072** [**0.0052**, **0.0092**]	184575
2	Mobility	0.0006 [−0.0009, 0.0020]	**0.0151** [**0.0090**, **0.0213**]	182843
	Contiguity	0.0005 [−0.0010, 0.0020]	**0.0041** [**0.0021**, **0.0061**]	182829
3	Mobility	**−0.0020** [**−0.0034**, **−0.0006**]	**0.0065** [**0.0002**, **0.0127**]	181150
	Contiguity	**−0.0023** [**−0.0038**, **−0.0008**]	**0.0022** [**0.0001**, **0.0042**]	181105
7	Mobility	**−0.0015** [**−0.0029**, **−0.0002**]	**0.0107** [**0.0043**, **0.0170**]	175051
	Contiguity	−0.0011 [−0.0026, 0.0003]	0.0010 [−0.0011, 0.0030]	175046

Key findings

- δ_2 (spillover) – **consistently positive and significant** across all lags; mobility from connected areas raises local cases.
- δ_1 (direct) – **near zero or negative**, significantly negative at lags 3 & 7; best interpreted as residual time-dependent confounding, not protection.
- Mobility network yields **larger** spillover estimates than contiguity.

Lags 4, 5, 6 (not shown) are fully consistent with the pattern above: δ_2 positive and significant; δ_1 weak / negative.

4 CONCLUSION & DISCUSSION

- δ_1 negative → **time-dependent confounding** (cases suppress mobility; red paths in Fig 2) . Standard GPS cannot adjust for this feedback.
- **Further extensions:** Marginal structural models (MSMs) / g-methods.
- **Limitations:** unmeasured confounding, endogenous network, restrictive interference.

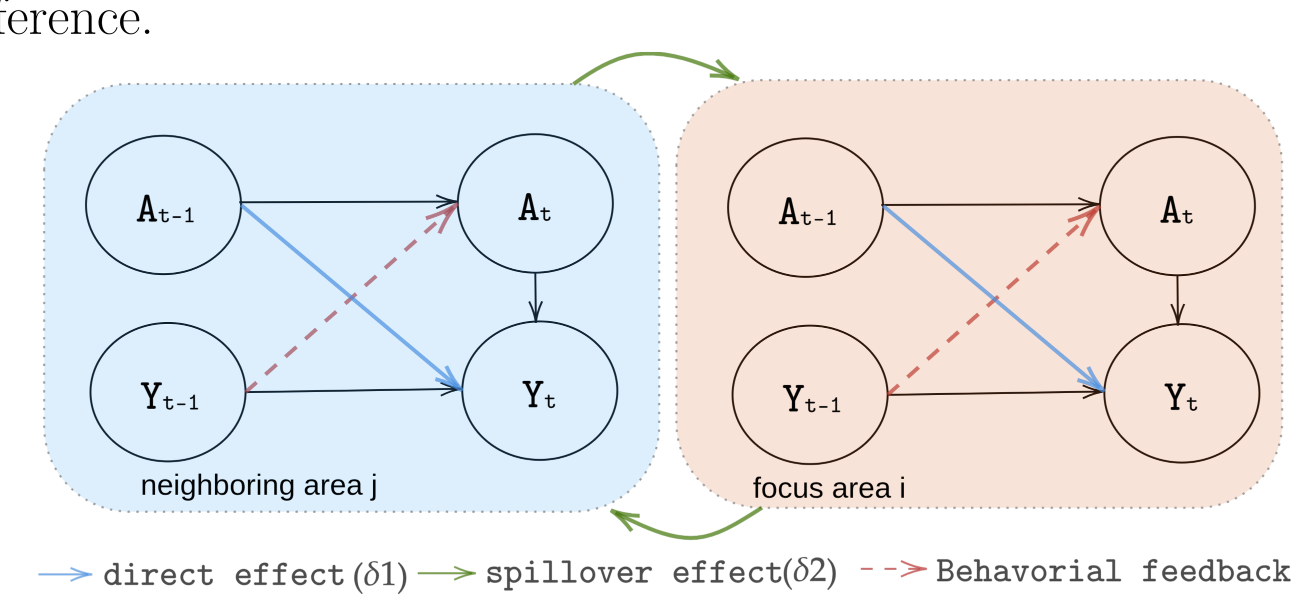

Figure 2: Causal feedback loop. Past cases reduce mobility (red), biasing direct effect.

References

[1] Advan Research. Foot traffic / weekly patterns plus [dataset], 2025. DOI: https://doi.org/10.82551/C103-N851.

[2] A. Giffin, B. J. Reich, S. Yang, and A. G. Rappold. Generalized Propensity Score Approach to Causal Inference with Spatial Interference. *Biometrics*, 79(3):2220–2231, September 2023.