Inferential clustering reveals administrative boundaries in Austrian migration networks

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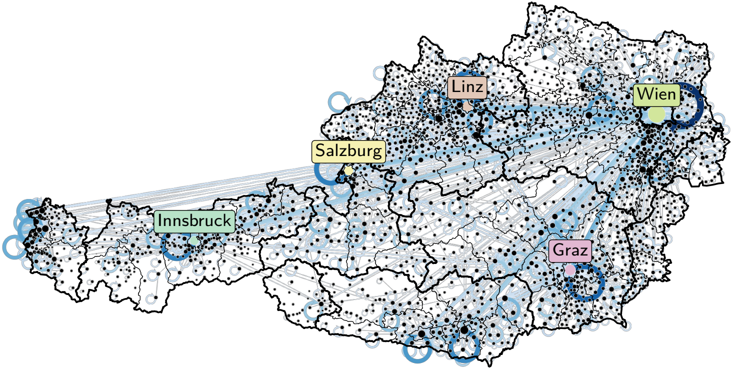
Martina Contisciani

Central European University, Vienna, AT

with Thomas Robiglio, Márton Karsai, Tiago P. Peixoto

Austrian Internal Migration Network[1]

- Node i: municipality ($N = 2093$)
- *Directed and weighted* edge x_{ij}: relocations ($E \sim 70K$)
- Years 2002-2021, aggregated annually



[1] https://data.statistik.gv.at/

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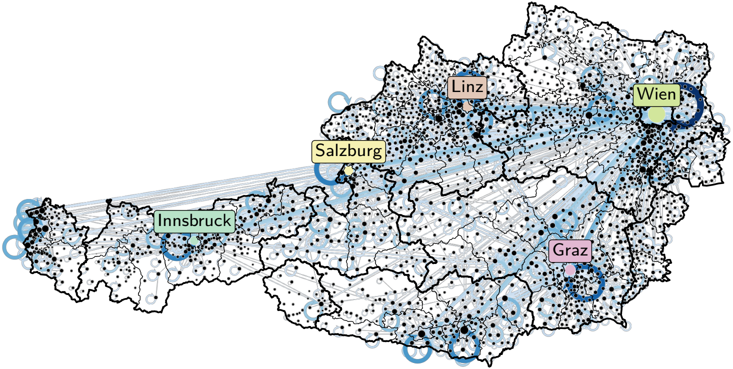

We analyse twenty distinct networks that capture migration flows for each year. The results in this presentation refer to the year 2013.

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Gravity Model

The rate of movement (I_{ij}) between two locations tends to increase with the product of their population densities (p_i, p_j), and to decay with their distance (d_{ij}):

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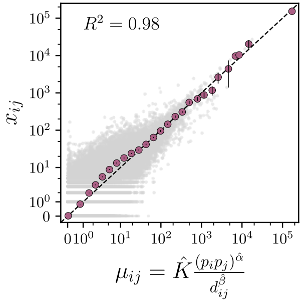

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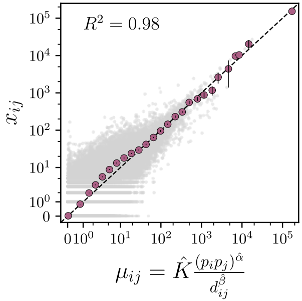


But, hidden discrepancies in relation to geographical and urban-rural information.

Weighted Stochastic Block Model[2]

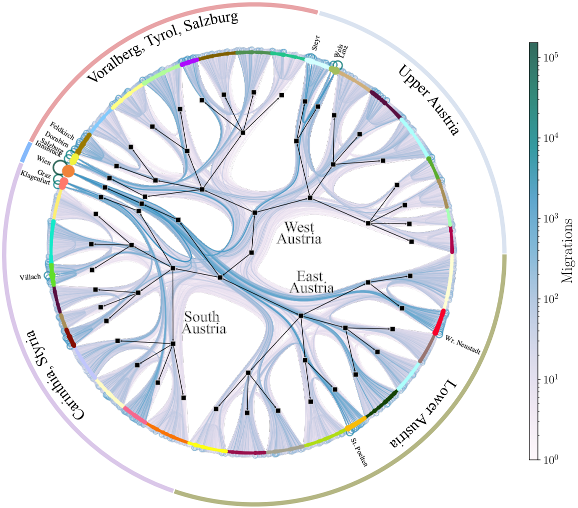
Given a partition $\mathbf{b}$ of the municipalities into B groups, the migrations between two locations are sampled only according to their group memberships:

$$P(\mathbf{x} \mid \theta, \mathbf{b}) = \prod_{ij} P(x_{ij} \mid \theta_{b_i, b_j})$$

- $P(x_{ij} \mid \theta_{b_i, b_j})$ is a kernel distribution conditioned only on the groups
- Number of groups B inferred from data
- Hierarchical partition

[2] T. P. Peixoto, Physical Review E 97, 012306 (2018)

Inferred Hierarchical Partition



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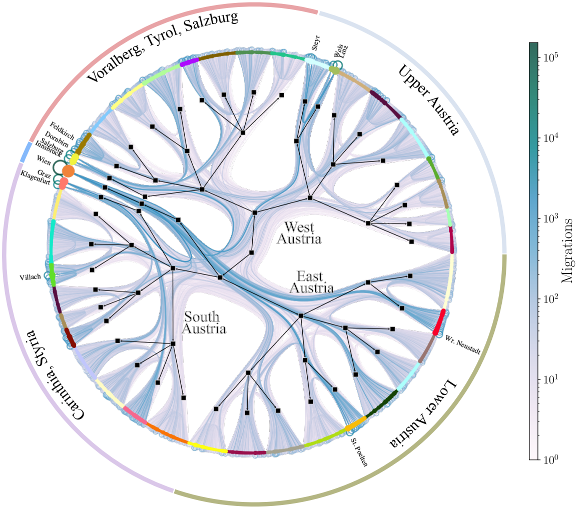
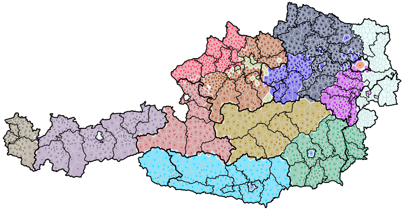


Inferred groups at level $l = 1$



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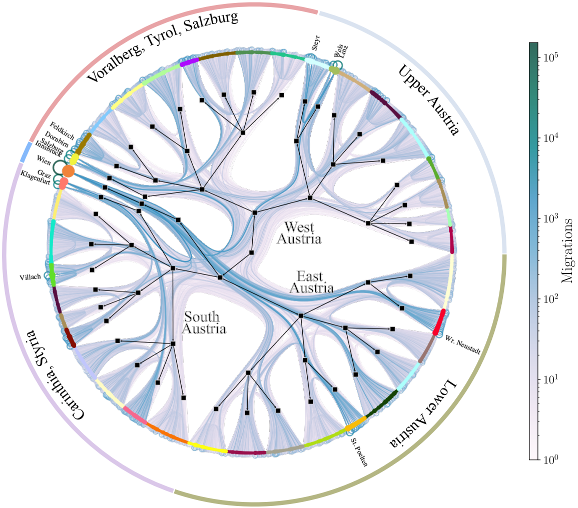
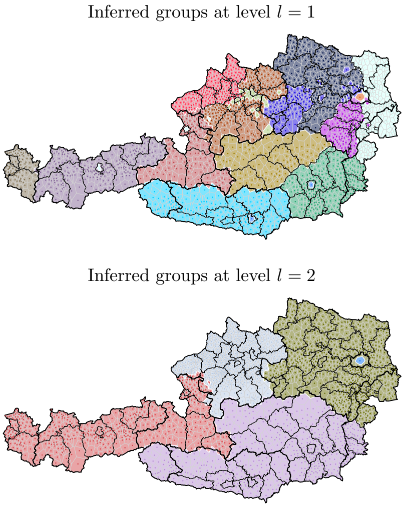
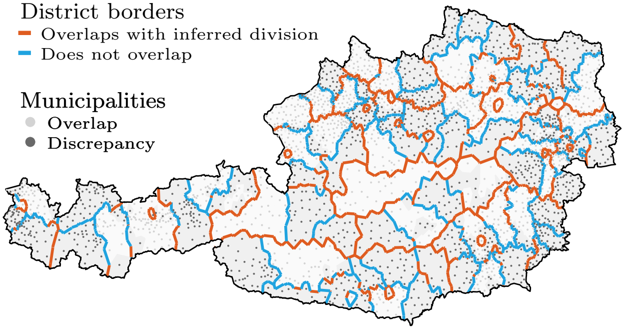




Administrative Boundaries

Around 47% of the district borders coincide exactly with the boundaries between the inferred groups, and the same holds for $\sim 72\%$ of the federal state boundaries.



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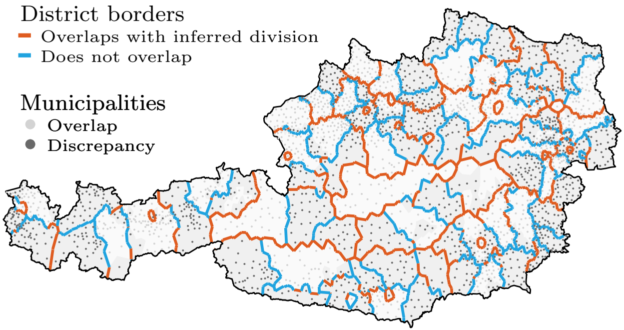
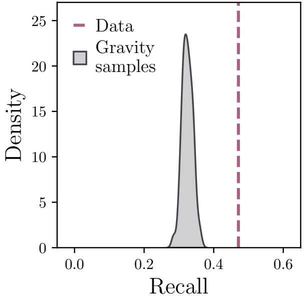
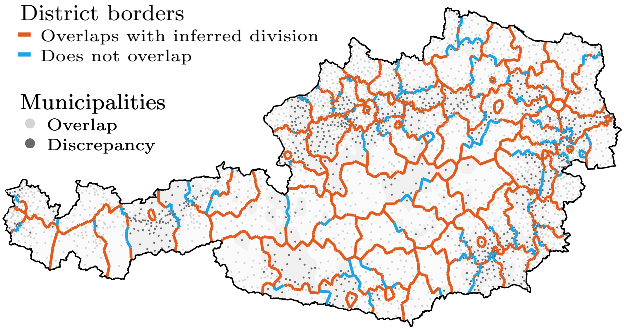
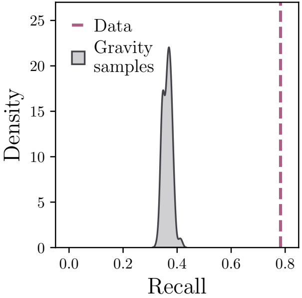




Administrative Boundaries in Binary Network

District-level effects become more visible when the magnitudes are excluded, and the match between district borders and inferred boundaries reaches 78%.





Main Takeaways

- Migration flows in Austria are driven by **more than gravity**
- Inferential clustering reveals effects of:
  - ◇ **administrative boundaries**
  - ◇ **urban-rural divide**
- Patterns consistent over twenty years

Main Takeaways

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Next step of the MOMA project: provide explanations of the observed patterns

Thank you!

Stay tuned... Soon on arXiv!

contiscianim@ceu.edu
mcontisc.github.io

Thomas Robiglio

Márton Karsai

Tiago P. Peixoto

Gravity Model

The migration flows between two locations are modelled as Poisson-distributed random variables

$$I_{ij} \sim \mathrm{Pois}(\mu_{ij})$$

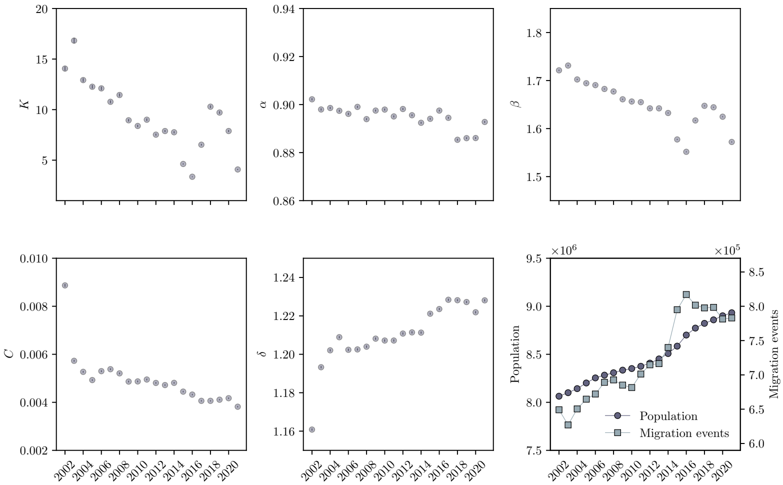
with

$$I_{ij} = \begin{cases} x_{ij} + x_{ji} & \text{if } i \neq j \\ x_{ii} & \text{if } i = j \end{cases} \quad \text{and} \quad \mu_{ij} = \begin{cases} K \frac{(p_i p_j)^\alpha}{d_{ij}^\beta} & \text{if } i \neq j \\ C p_i^\delta & \text{if } i = j \end{cases}.$$

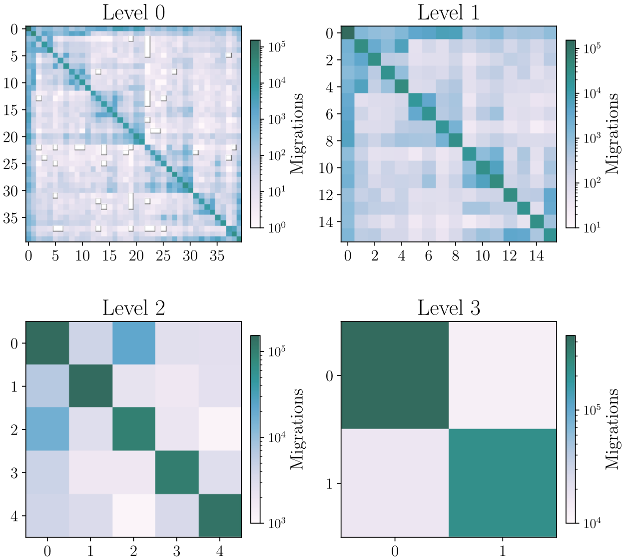
To generate directed synthetic networks, we sample the edge weights $\hat{x}_{ij}$ from the estimated Poisson gravity model rates as

$$\hat{x}_{ij} \sim \begin{cases} \mathrm{Pois}(\mu_{ij}/2) & \text{if } i \neq j \\ \mathrm{Pois}(\mu_{ii}) & \text{if } i = j \end{cases}.$$

Inferred Parameters Gravity Model

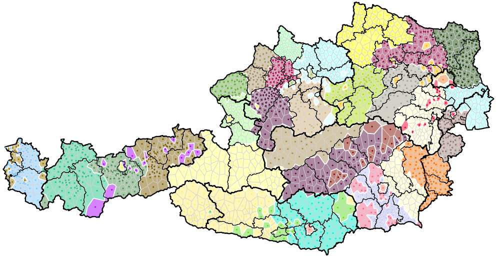


Inferred Affinity Matrices

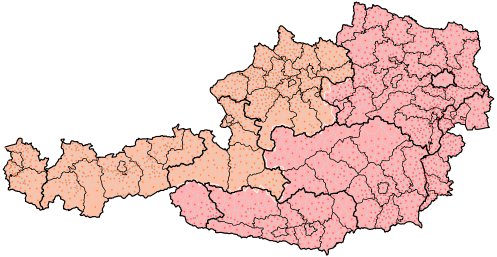


Inferred Partitions

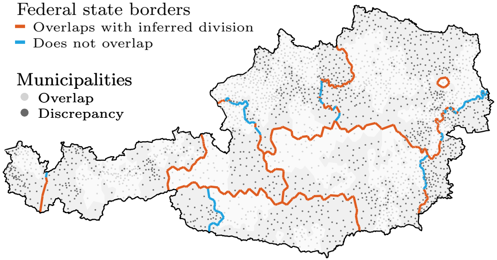
Inferred groups at level $l = 0$

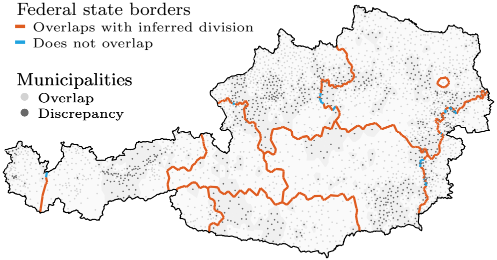


Inferred groups at level $l = 3$

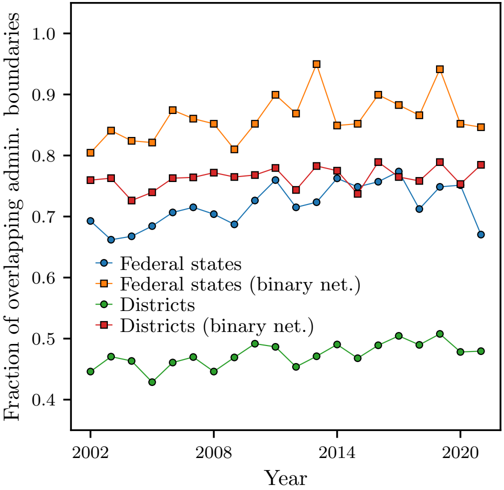


Federal State Boundaries

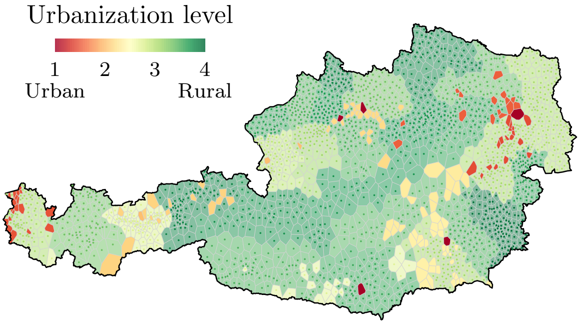


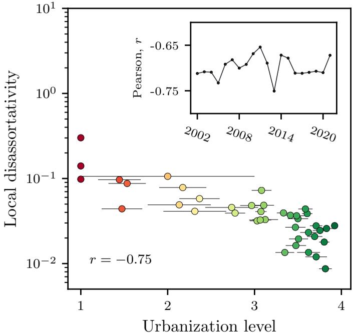


Administrative Boundaries Over Time



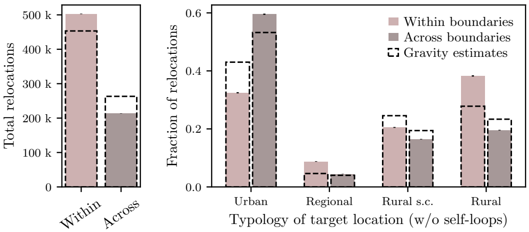
Urban-Rural Classification



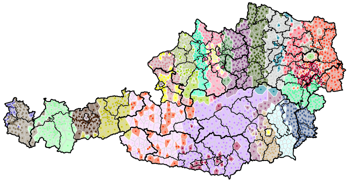


Additional Results

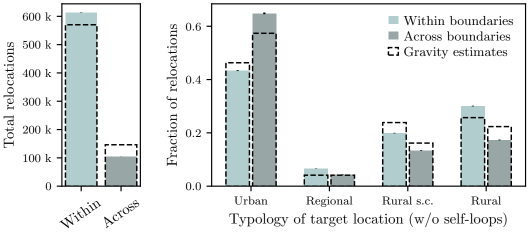
(a) Migration volumes in relation to districts



(b) Inferred groups from a gravity model sample



(c) Migration volumes in relation to federal states



(d) Comparison with gravity model samples