HOUSING MARKET AND MIGRATION REVISITED

A multilevel gravity model for Dutch regions

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Housing market and interregional migration: why bother?

- Dutch housing market: tight and regulated
  - large shortage of housing
  - large yearly prices increases ($\approx 5\% - 9\%$ annually)
  - decrease in housing transactions
  - large regional variation

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- Large literature of external effects of home-ownership (Dietz and Haurin, 2003)
    - negative: migration (by increased moving costs) and on aggregate labour market performance (Oswald, 1996, 1999)

My contributions to the literature

- Large empirical (economic) literature on impact home-ownership as drivers of interregional migration, but:
  - usually concerns marginal effect of home-ownership
  - less attention to predictions for the whole network
- Literature on impact of social renting on migration flows is scarce (De Graaff et al., 2009)
  - In the Netherlands social renting is a large phenomenon ($\approx$ 24% of total housing stock)
  - Social renting rights only valid within city
  - Social renting is an urban phenomenon (e.g. $\approx$ 40–50% in Amsterdam)

So, this paper

Does what? Revisits the impact of housing market structure (with focus on social renting) on Dutch interregional migration flows using a multilevel gravity model

- UK context by Congdon (2010)
- social relations model *cf.* Koster and Leckie (2014)
- *Statistical Rethinking* from McElreath (2020)
- `ggplot2` code from Solomon Kurz (2020)

Aim To model the impact of housing market structure on the whole network of interregional migration flows

Why a multilevel approach for migration?

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Observed migration flows Migration between i and j with friction (e.g., distance) attributes (obs $= R^2 - R$)

$$\text{REGION}_i \xrightarrow{\mathbf{X}_{ij}} \text{REGION}_j$$

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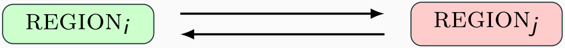
Observed flows between region dyads migration from $i \to j$ is correlated with migration from $j \to i$ (obs $= \frac{R^2 - R}{2}$)



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- Simultaneous modeling at various levels (e.g., cities, regions, flows, individuals)
  - no two-stage models anymore
  - precision (standard errors) is correct

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- Hierarchical, mixed effects, varying intercept/parameter, shrinkage, partial pooling models
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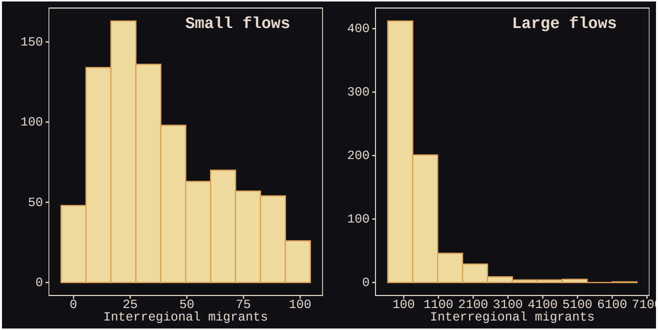
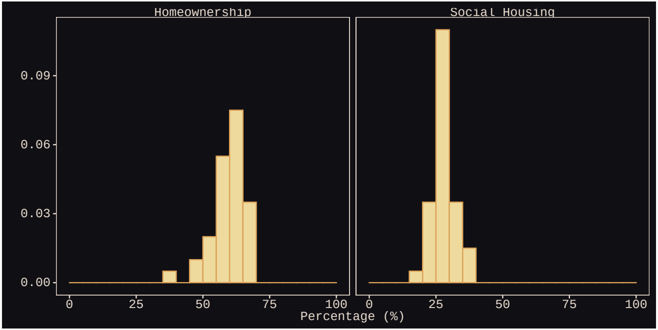
- Simultaneous modeling at various levels (e.g., cities, regions, flows, individuals)
    - no two-stage models anymore
    - precision (standard errors) is correct
- Partial pooling: For example, origin specific effects are drawn from a distribution: usually $\sim$ Normal(α, σ)
    - $\sigma \longrightarrow 0$: complete pooling
    - $\sigma \longrightarrow \infty$: no pooling (fixed effects)

Data: migrations flows in 2018



- Panel for the period 2012–2018
- Migration flows between 40 Dutch regions ($1,560$ flows per year)
- Variance $\gg$ mean: over-dispersion

Data: regional housing structure in 2018



- Positive correlation between population and share social renting (0.46)
- Negative correlation between share social renting and share home-ownership (−0.88)

Data: regional housing structure in 2018 (cont.)

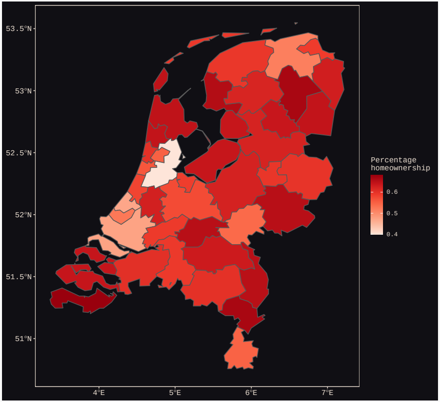


Figure 1: Share of homeownership

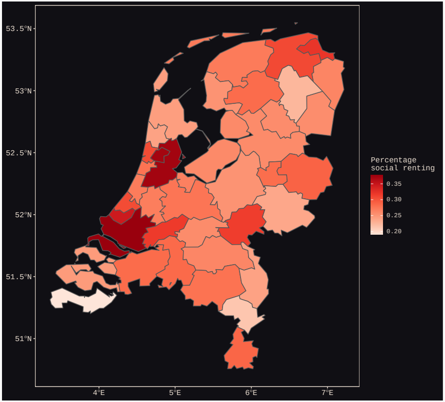


Figure 2: Share of social renting

Modeling framework: traditional gravity modeling

$$\log(\text{Migrants}_{ij}) = o_i + d_j + \gamma \log(\text{dist}_{ij}) + \epsilon_{ij}$$

Origin and destination specific fixed effects for multilateral resistance (Anderson and Van Wincoop, 2003), but:

- what about zeros in Migrants_{ij}?
- how to incorporate housing structure in the presence of o_i and d_j?
- over-dispersion and heteroskedasticity (Silva and Tenreyro, 2006)

Poisson versus negative binomial[1]

- Counts of migrants

- With Poisson & regional effects of origin and destination the following origin and destination constraints automatically hold

$$\sum_{j=1}^{R} \widehat{\text{Migrants}}_{ij} = O_i \qquad \sum_{i=1}^{R} \widehat{\text{Migrants}}_{ij} = D_j$$

- Does not apply with negative binomial

- Multilevel model accounts for dispersion

[1] *We urge researchers to resist the siren song of the Negative Binomial (Head and Mayer, 2014)*

Modeling framework: multilevel gravity modeling

$$\text{Migrants}_{ij} \sim \text{Poisson}(\lambda_{ij})$$

$$\text{Migrants}_{ji} \sim \text{Poisson}(\lambda_{ji}) \qquad \text{(flow of migrants)}$$

Modeling framework: multilevel gravity modeling

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\text{Migrants}_{ji} &\sim \text{Poisson}(\lambda_{ji}) && \text{(flow of migrants)} \\
\log(\lambda_{ij}) &= \alpha + o_i + d_j + \text{dyad}_{ij} + && \text{(varying effects)}
\end{aligned}$$

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\begin{pmatrix} o_i \\ d_i \end{pmatrix} &\sim \text{MVNormal}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_o^2 & \sigma_o \sigma_d \rho \\ \sigma_o \sigma_d \rho & \sigma_d^2 \end{pmatrix} \right) \\
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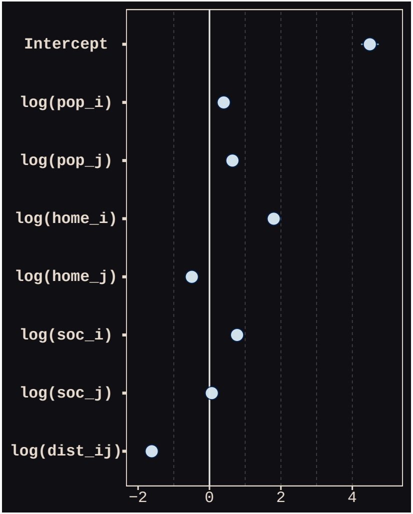
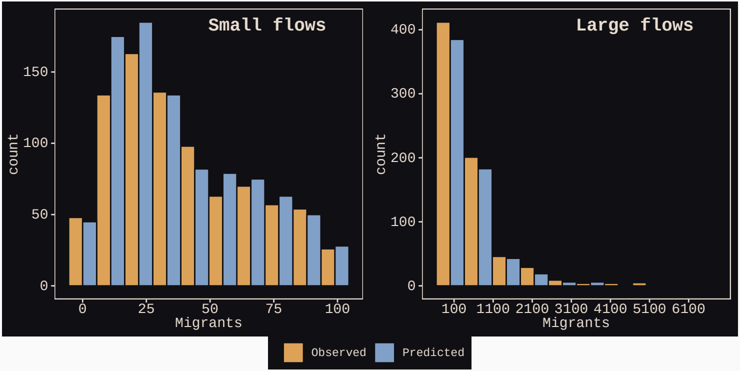
& && \text{(varying dyad effects)}
\end{aligned}
$$

Estimation results

Parameter	mean	sd
Intercept (α)	4.49	0.15
$\log(\text{pop}_i)$	0.40	0.04
$\log(\text{pop}_j)$	0.64	0.03
$\log(\text{home}_i)$	1.80	0.10
$\log(\text{home}_j)$	-0.50	0.09
$\log(\text{soc}_i)$	0.77	0.07
$\log(\text{soc}_j)$	0.06	0.07
$\log(\text{dist}_{ij})$	-1.62	0.03

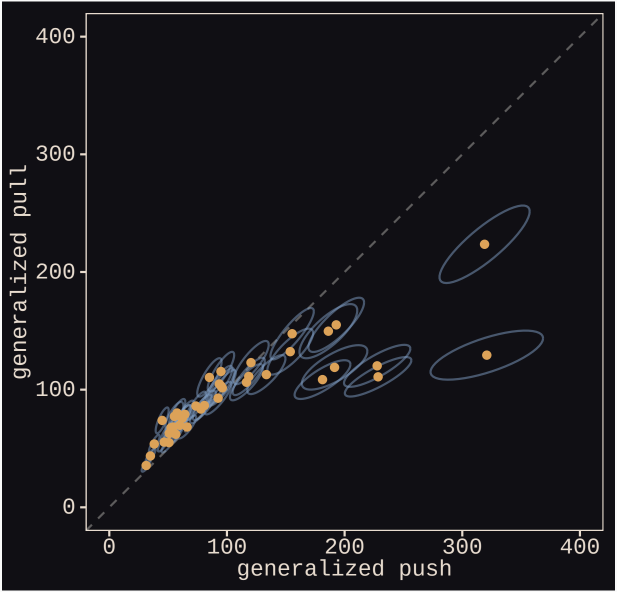


Observed versus predicted flows (correlation ≈ 0.99)

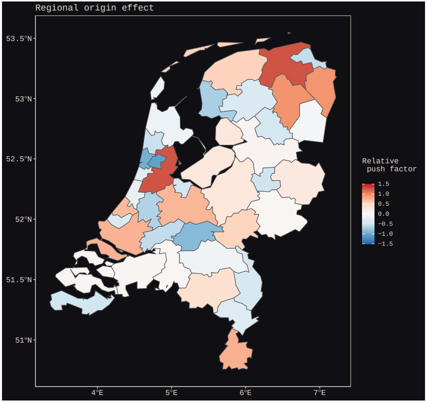


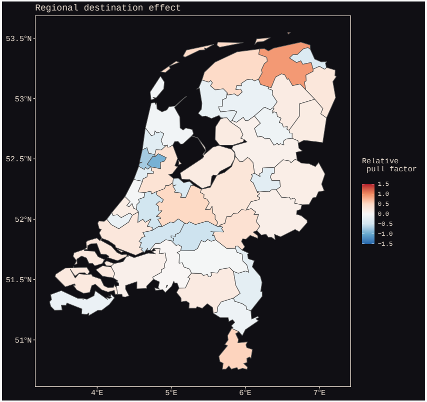
- maximum observed flow: 6,555
- maximum predicted flow: 4,704

Correlation between origin and destination $\rho = 0.88$

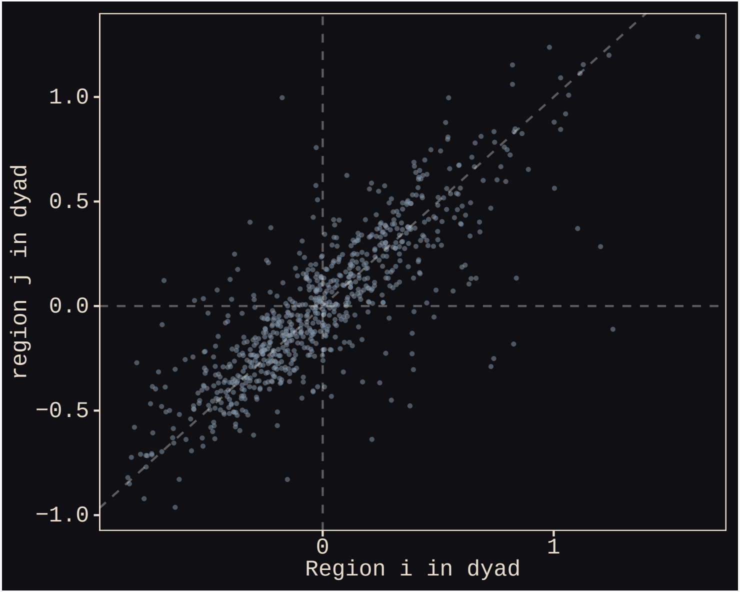


Asymmetric push and pull factors





Dyad specific effects $\rho = 0.8$



Sensitivity checks

Results are robust to

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- spatial autocorrelation in regional effects:

$$\begin{aligned} o_i, d_j &\sim \text{MVNormal}(0, \mathbf{K}) \\ \mathbf{K}_{ij} &= \eta^2 \exp(-\rho^2 \mathbf{D}_{ij}) \end{aligned}$$

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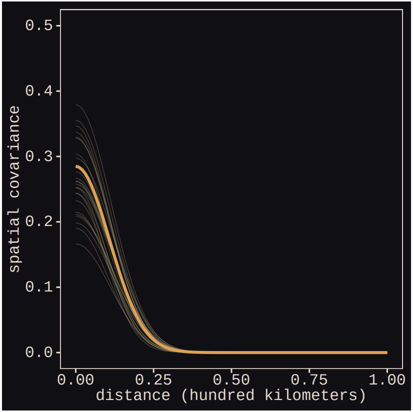
Modest spatial autocorrelation



Conclusions

Flexibel and powerful Bayesian multilevel gravity model:

- housing structure asymmetric impact on migration
  - positive on push/negative on pull
  - push factor large in large cities
- impact social renting smaller than homeowership (Boyle, 1998)
  - social housing is like a different ball game
- tight housing market

Now what?

- model performance is quite good
  - out-of-sample prediction
  - long-distance migration (dyad effects)

Supplementary materials

Paper, presentation, data and code can be retrieved from the project's GitHub page:

https://github.com/Thdegraaff/migration_gravity

Thank you!

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