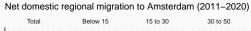
URBAN EXODUS OR RURAL SHRINKAGE?

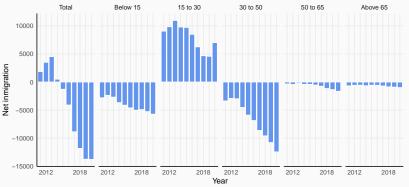
REGIONAL MIGRATION AND ATTRACTIVENESS IN A TIGHT DUTCH HOUSING MARKET

Thomas de Graaff March 17, 2022

Vrije Universiteit Amsterdam Tinbergen Institute Amsterdam

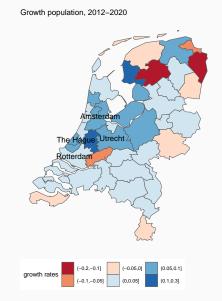
Urban Exodus?





Dutch population growth 2012–2020

- NUTS-3 regions
 - originally (1970) labour market regions
- Last decade:
 - homogeneous population growth
 - few peripheral regions decline
- Domestic migration
 - slightly more within regions than between
 - growth is the same



Tight Dutch housing market

- Average housing price:
 €410,000
- Change last year +20%
- Waiting list social renting Amsterdam: 13 years
- Large shortage of housing
- Decrease in housing transactions







Housing market, urban regions and interregional migration: why bother?

- Possible drivers of urban out-migration?
 - suburbanisation of poverty (Hochstenbach and Musterd, 2018)
 - crowding-out of the housing market by short-term rentals (Koster et al., 2021)
 - Influx of high-skilled migrants (Beckers and Boschman, 2019)

Housing market, urban regions and interregional migration: why bother?

- Possible drivers of urban out-migration?
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 - Influx of high-skilled migrants (Beckers and Boschman, 2019)
- Large literature on external effects of home-ownership (Dietz and Haurin, 2003)
 - negative: moving costs (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 for the whole network (e.g., Amsterdam effect)
- 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/region
 - \bullet Social renting is an urban phenomenon (e.g. \approx 30–40% in Amsterdam)

So, this paper

- **Does what?** Estimates the impact of housing market structure 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 Kurz (2020)
 - **Aim** To simultaneously assess the impact of housing market structure and region specific effects on domestic migration flows

There are at least two levels in migration (I use three)

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

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Observed push & pull factors Attributes of i and j (obs = R)





There are at least two levels in migration (I use three)

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

Observed push & pull factors Attributes of *i* and *j* (obs = R)



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

$$\begin{array}{c} \text{REGION}_i \end{array} \longrightarrow \begin{array}{c} \\ \\ \end{array}$$

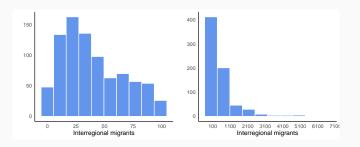
 Hierarchical, mixed effects, varying intercept/parameter, shrinkage, partial pooling models

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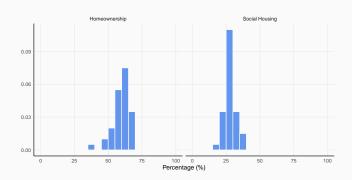
- Hierarchical, mixed effects, varying intercept/parameter, shrinkage, partial pooling models
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- Simultaneous modeling at various levels (e.g., cities, regions, flows, individuals)
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- Partial pooling: For example, origin specific effects are drawn from a distribution: $o_i \sim \mathcal{N}(0, \sigma)$
 - $\sigma \longrightarrow 0$: complete pooling
 - $\sigma \longrightarrow \infty$: no pooling (fixed effects)

Data: migrations flows in 2018



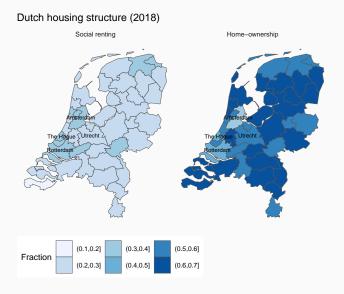
- Panel for the period 2012–2020
 - estimation: 2012-2019
 - out-of-sample prediction: 2020
- Migration flows between 40 Dutch regions
- Variance ≫ mean: over-dispersion

Data: regional housing structure in 2018



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

Data: regional housing structure in 2018 (cont.)



Modeling framework: traditional gravity modeling

$$ln(Migrants_{ij}) = o_i + d_j + \gamma ln(dist_{ij}) + \epsilon_{ij}$$

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

- what about zeros in Migrants;;?
- how to incorporate housing structure in the presence of o_i and d_i?
- over-dispersion and heteroskedasticity (Silva and Tenreyro, 2006)

Poisson versus negative binomial¹

- Counts of migrants
- Constraints should hold

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

- poisson: ✓
- negative binomial: X
- multilevel structure controls for overdispersion

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

 $\mathsf{Migrants}_{ijt} \sim \mathsf{Poisson}(\lambda_{ijt})$

(flow of migrants)

$$\begin{split} \mathsf{Migrants}_{ijt} \sim & \mathsf{Poisson}(\lambda_{ijt}) & (\mathsf{flow} \ \mathsf{of} \ \mathsf{migrants}) \\ & \mathsf{In}(\lambda_{ijt}) = \alpha + o_i + d_j + t_t + \mathsf{dyad}_{ij} + \\ & \beta_1 \, \mathsf{In}(\mathsf{pop}_{it}) + \beta_2 \, \mathsf{In}(\mathsf{pop}_{jt}) + \gamma \, \mathsf{In}(\mathsf{dist}_{ijt}) + \\ & \beta_3 \, \mathsf{In}(\mathsf{home}_{it}) + \beta_4 \, \mathsf{In}(\mathsf{home}_{jt}) + \beta_5 \, \mathsf{In}(\mathsf{soc}_{it}) + \beta_6 \, \mathsf{In}(\mathsf{soc}_{jt}) \\ & & (\mathsf{linear} \ \mathsf{model}) \end{split}$$

$$\begin{split} & \operatorname{\mathsf{Migrants}}_{ijt} \sim \operatorname{\mathsf{Poisson}}(\lambda_{ijt}) & (\mathsf{flow\ of\ migrants}) \\ & \operatorname{\mathsf{In}}(\lambda_{ijt}) = \alpha + o_i + d_j + t_t + \operatorname{\mathsf{dyad}}_{ij} + \\ & \beta_1 \operatorname{\mathsf{In}}(\operatorname{\mathsf{pop}}_{it}) + \beta_2 \operatorname{\mathsf{In}}(\operatorname{\mathsf{pop}}_{jt}) + \gamma \operatorname{\mathsf{In}}(\operatorname{\mathsf{dist}}_{ijt}) + \\ & \beta_3 \operatorname{\mathsf{In}}(\operatorname{\mathsf{home}}_{it}) + \beta_4 \operatorname{\mathsf{In}}(\operatorname{\mathsf{home}}_{jt}) + \beta_5 \operatorname{\mathsf{In}}(\operatorname{\mathsf{soc}}_{it}) + \beta_6 \operatorname{\mathsf{In}}(\operatorname{\mathsf{soc}}_{jt}) \\ & & (\operatorname{\mathsf{linear\ model}}) \\ & \left(\begin{matrix} o_i \\ d_j \end{matrix} \right) \sim \mathcal{N} \left\{ \left(\begin{matrix} 0 \\ 0 \end{matrix} \right), \left(\begin{matrix} \sigma_i^2 & \rho_{ij} \\ \rho_{ij} & \sigma_i^2 \end{matrix} \right) \right\} & (\text{regional\ varying\ effects}) \end{split}$$

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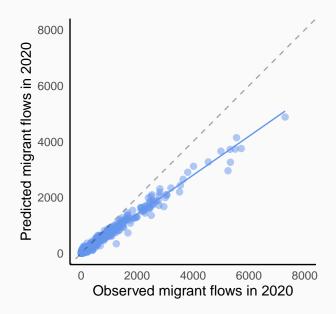
Main Estimation results

parameter	origin (push)	destination (pull)
In(population)	-0.10	0.70
In(% homeownership)	-1.73	1.37
In(% social renting)	-0.40	0.99
In(household size)	5.46	-2.35
In(% western immigrants)	-0.14	-0.01
intercept		3.89
migrants flow:		
In(distance)		-1.63
standard deviations:		
origin		0.67
destination		0.44
dyad		0.39
correlation		
origin-destination		0.78
dyad		0.80

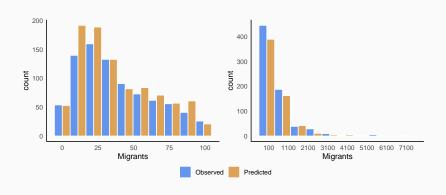
Bold: 89% credible intervals do not include zero

Samples are drawn using the NUTS sampler from STAN using 4 chains, each with $4{,}000$ iterations and $1{,}000$ warm-up samples

Out-of-sample prediction for 2020 ($R^2 = 0.98$)



Out-of-sample prediction for 2020 (cntd.)



Correlation patterns

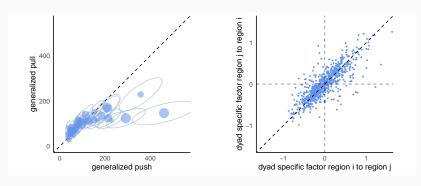
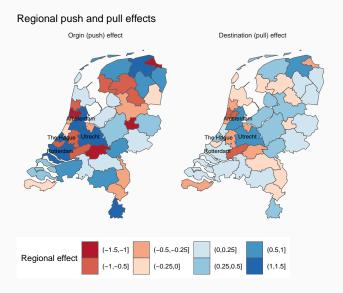
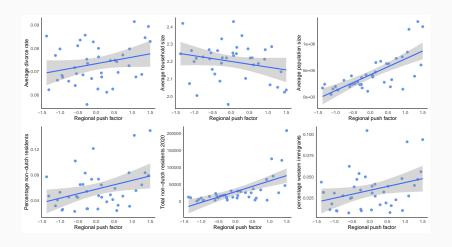


Figure 1: Correlation (0.78) between unobserved push and pull factors region (left) and flows (correlation = 0.8) within dyad pairs (right)

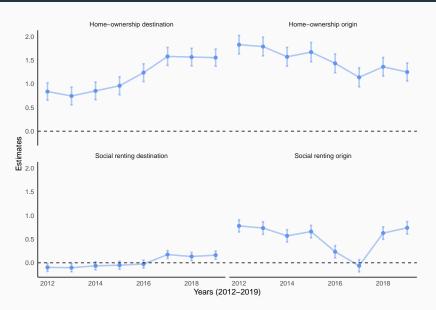
Asymmetric push and pull factors



Determinants of push factors?



Sensitivity check: temporal stability?



Sensitivity check: spatial autocorrelation

• spatial autocorrelation in regional effects:

$$o_i, d_j \sim \text{MVNormal}(0, \mathbf{K})$$

 $\mathbf{K}_{ij} = \eta^2 \exp(-\rho^2 \mathbf{D}_{ij})$

• results remain robust

Sensitivity check: spatial autocorrelation

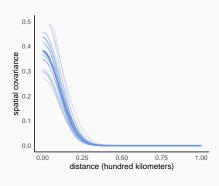
• spatial autocorrelation in regional effects:

$$o_i, d_j \sim \text{MVNormal}(0, \mathbf{K})$$

 $\mathbf{K}_{ij} = \eta^2 \exp(-\rho^2 \mathbf{D}_{ij})$

• results remain robust

Modest spatial autocorrelation



Conclusions

Main results:

- home-ownership has a positive impact on regional domestic migration
 - social renting to a lesser extent
- large urban areas have large push effects
 - effect is different from housing market structure
 - similar to and larger than push effects in periphery

Speculation:

- home-ownership is a proxy for satelite communities close to major urban areas?
- tourism, short stay (high-skilled), and large housing investment companies drive natives out?

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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