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Conference Paper

Job Opportunities, Amenities, and Variable Distance-Deterrence Elasticities: An Empirical Model of Inter-Municipal Migration in Belgium

46th Congress of the European Regional Science Association: "Enlargement, Southern Europe and the Mediterranean", August 30th - September 3rd, 2006, Volos, Greece

Provided in Cooperation with:
European Regional Science Association (ERSA)

Job opportunities, amenities, and variable distance-deterrence effects: an empirical model of inter-municipal migration in Belgium

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Abstract

This paper investigates inter-municipal migration flows in Belgium using a Poisson gravity model, taking into account the *variation* in the distance-deterrence effect. Besides distance, the model also includes some municipal-specific factors as explanatory variables. In addition, the model accounts for unobserved origin/destination characteristics. The model is tested using aggregate, cross-sectional, data on migrations between the municipalities of the Belgian province of Limburg, over the period 1998-2003. To overcome the problem of under-determinacy, we use the method of Generalized Cross-Entropy estimation. A number of findings stand out. Firstly, we find evidence of a U-shaped relationship between the distance-deterrence elasticity and distance. Secondly, distance between origin and destination reinforces (attenuates) the pull effect of local employment opportunities (local amenities). This finding may reflect a shift in the composition of migration flows from residential migration to labor migration as distance increases. Finally, the spatial distribution of the net pull effects of unobserved factors seems to coincide with proximity to major roads and railway stations.

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1. Introduction

The literature on migration points out two main reasons for migration (e.g., Ghatak et al., 1996; Mueser and Graves, 1995). First, from a human-capital point of view migration is treated as an investment, and the decision to move is taken in order to improve the workers' expected income and/or employment opportunities (*labor* migration). Second, migration can be viewed from a "consumption" standpoint, in which case people move because they look for attract (*residential* migration). However, empirical evidence of factors that influence the "composition" of migration flows is limited (Shioji, 2001) – e.g., in terms of the reasons for migration, and most empirical studies fail to account for the heterogeneous ways in which distance (or, the *perception* of distance) may induce "selective" in- or out-migration. Since the composition of migration cannot be observed directly from aggregate (census) data, any test has to be necessarily indirect.

In this paper we are specifically concerned with: (a) the effects of various factors, including the spatial structure and several origin-destination characteristics (push and pull factors); (b) the effects of unobserved (unmeasured) origin-destination factors; (c) the variability (spatial heterogeneity) in distance-decay elasticities; (d) how the pull effects of local amenities (residential migration) and local labor market characteristics (labor migration) in destinations are affected by distance.

Specifically, we develop a simple (unconstrained) Poisson gravity model of migration, using cross-sectional data (e.g., Fotheringham and O'Kelly, 1989; Sen and Smith, 1995; Shen, 1999). We use *gross* migration flows (rather than net migration), because such data contain more information and allow for a clear identification of underlying mechanisms. The model is estimated using the Generalized Cross-Entropy (GCE) method (e.g., Golan et al., 1996). This method allows us to overcome the problem of under-determinacy ("ill-posed" nature of the estimation problem), due to the fact that the number of unknown coefficients is larger than the number of observations.

The paper is organized as follows: Section 2 presents the basic Poisson gravity model. Section 3 introduces some extension of this model, including spatial cross-regressive terms, variable distance-decay elasticities, unobserved (unmeasured) origin-destination-specific heterogeneity, and distance-dependent pull effects. Section 4 points the problem of under-determinacy, and proposes the GCE method for estimation. Section 5 discusses the empirical application. Section 6 concludes the paper.

2. Poisson gravity model

Spatial-interaction or gravity models are popular tools for predicting migration flows between spatial units. The main underlying assumption of these models is that migration depends on factors related to region *i* (origin), on factors related to region *j* (destination), and on the distance between *i* and *j*.

The standard gravity model, including structural covariates (e.g., socio-economic and demographic push and pull factors) is

$$\ln m_{ij} = \alpha_0 + \sum_{k=1}^{K} \alpha_{1,k} \ln x_{i,k} + \sum_{h=1}^{H} \alpha_{2,h} \ln x_{j,h} + \beta \ln d_{ij} + \varepsilon_{ij} \tag{1}$$

where m_{ij} is the gross migration flow from origin *i* to destination *j*, $x_{i,k}$ are *push* factors at origin *i*, $x_{j,h}$ are *pull* factors at destination *j*, and d_{ij} is the physical distance between origin *i* and destination *j*.

A Poisson gravity model, however, is a more realistic description of the migration process than the traditional log-linear model (e.g., Shen, 1999):[1]

$$m_{ij} = \exp\left\{ \alpha_0 + \sum_{k=1}^{K} \alpha_{1,k} \ln x_{i,k} + \sum_{h=1}^{H} \alpha_{2,h} \ln x_{j,h} + \beta \ln d_{ij} \right\} + \varepsilon_{ij} \tag{2}$$

The Poisson model in equation (2) is our preferred model, since it provides a better fit. The model in equation (1) may produce a high R^2 calculated by using the logs of the number of migrants, but a low R^2 if calculated by using the (un-logged) numbers of migrants.

[1] Rather than estimating the parameters with maximum-likelihood techniques, we treat the Poisson model as a simple non-linear regression (Greene, 2003, p. 740). We also append an error term (i.e., we extend the model to incorporate random effects), which allows the variance of the dependent variable to exceed its mean value (over-dispersion). Note that choosing the exponential function has the advantage that it assures non-negativity.

3. Extensions of the gravity model

3.1 Spatial cross-regressive term

It is a common practice in spatial interaction modeling to include a variable that measures the centrality of destinations (e.g., Fortheringham and O'Kelly, 1989; Sá et al., 2004). Here, however, we adopt a rather non-standard approach, and include a *spatial cross-regressive term* (e.g., Rey and Montouri, 1999), measuring the pull effect of some factors (e.g., local supply of amenities or local labor-market conditions) in *nearby* destinations:

$$\tilde{x}_j = \sum_{j' \neq j}^{N} w_{ij} x_{j'} = \sum_{j' \neq j}^{N} \frac{x_{j'}}{d_{jj'}} \tag{3}$$

where $\tilde{x}_j$ is the "spatially lagged" value of x_j, $d_{jj'}$ is the distance between the destinations j and j', and $x_{j'}$ is a measure of the attractiveness of (pull factor in) destination j'. [Note that instead of using the inverse distances as weights, we could also have used w_{ij} as the elements of a row-standardized contiguity matrix.] This yields the following model:

Model 1 $$m_{ij} = \exp\left\{ \alpha_0 + \sum_{k=1}^{K} \alpha_{1,k} \ln x_{i,k} + \sum_{h=1}^{H} \alpha_{2,h} \ln x_{j,h} + \sum_{h=1}^{H} \alpha_{3,j} \ln \tilde{x}_{j,h} + \beta \ln d_{ij} \right\} + \varepsilon_{ij} \tag{4}$$

where $\tilde{x}_{j,h}$ is are the spatially lagged variables at destination j.

To illustrate, consider the pull variable x_j at destination j along with the corresponding spatial cross-regressive term $\tilde{x}_j$ (i.e., an index of the same pull variable at other – surrounding – destinations j'), with associated coefficients α_2 and α_3, respectively. Assuming further that conditions in terms of supply of (service-based) amenities and/or employment opportunities are more favorable in urban centers, one can distinguish between four different scenarios, shown in table 1. For instance, in scenario 2, where $\alpha_2 < 0$ and $\alpha_3 > 0$, people would want to move to destinations that are geographically close to other destinations with more favorable conditions (local amenities and/or jobs), leading to suburbanization or rural-urban sprawl (e.g., Carrión-Flores and Irwin, 2004). Labor migrants may choose to move to rural-urban destinations and prefer to commute over short distances to their job locations in *nearby* urban centers. Also, residential migrants may choose to reside in rural-urban fringe areas and cover short or acceptable distances to get access to available service-based amenities in *nearby* urban centers. In both cases, this would reflect a *tension* between the demand for service-based amenities and/or the access to emerging jobs in urban destinations, on the one hand, and the demand for affordable houses/lower rents (labor migration) and/or open-space amenities, large-lot residential property (residential migration) associated with rural-urban destinations, on the other hand.

Table 1

3.2 Variable distance-decay elasticities

It is common practice to allow for region-specific distance-decay parameters (see, for example, Fotheringham and O'Kelly, 1989; Sá, et al., 2004; Fratianni and Kang, 2006). The geographical distribution of the locations makes that migrants from one location have to bridge longer distances than migrants from other locations. This is a form of *spatial heterogeneity* that would be ignored when assuming a single distance decay parameter for the entire region (e.g., Vermeulen, 2003).

Therefore, rather than using a uniform distance-decay parameter we account for spatial heterogeneity in the distance-deterrence effect by calibrating a model with origin-destination-specific coefficients β_{ij} for the distance variable.

Model 2 $$m_{ij} = \exp\left\{ \alpha_0 + \sum_{k=1}^{K} \alpha_{1,k} \ln x_{i,k} + \sum_{h=1}^{H} \alpha_{2,h} \ln x_{j,h} + \sum_{h=1}^{H} \alpha_{3,j} \ln \tilde{x}_{j,h} + \beta_{ij} \ln d_{ij} \right\} + \varepsilon_{ij} \quad (5)$$

Such a specification goes further than the common practice of allowing for location-specific distance-decay parameters; that is, through specifying either β_i or β_j (but not β_{ij}).

3.3 Unobserved heterogeneity of origins and destinations

Finally, some origin- or destination-specific processes may be in operation affecting origin- or destination-specific migration flows specifically (e.g., Shen, 1999, p. 1239). Thus, a two-level model, where level two can be defined on the basis of the origins ($\hat{\theta}_i$), or the destinations ($\hat{\eta}_j$), or both ($\hat{\theta}_i$ and $\hat{\eta}_j$):

Model 3

$$m_{ij} = \exp\left\{\alpha_0 + \theta_i + \eta_j + \sum_{k=1}^{K} \alpha_{1,k} \ln x_{i,k} + \sum_{h=1}^{H} \alpha_{2,h} \ln x_{j,h} + \sum_{h=1}^{H} \alpha_{3,j} \ln \tilde{x}_{j,h} + \beta_{ij} \ln d_{ij} \right\} + \varepsilon_{ij} \tag{6}$$

3.4 Short- and long-distance migration

In spatial interaction (migration) models, the number of migrants generally decreases with the distance between origin and destination. However, the explanatory variables work equally strong on short- and long-distance migrants flows. In other words, the parameters measuring the attraction of location-specific pull factors to migrants are independent of the distance they have to bridge. We doubt the validity of such an assumption.

Some authors (e.g., Vermeulen, 2003, p. 21) believe that the importance of pull factors in explaining aggregate migration flows, and hence their corresponding coefficients, changes with the distance between origin and destination: $\alpha_2(d_{ij}) = 1_{d_{ij} \le d^*}\, \alpha_{2,S} + 1_{d_{ij} > d^*}\, \alpha_{2,L}$. Pull factors triggering residential migration are thought to differ from pull factors triggering labor migration. For example, microanalysis of migration behavior in The Netherlands has shown that labor migrants move over larger distances than people that move for other reasons (Ekamper and Van Wissen, 2000). This would imply that the share of labor migrants in the aggregate migration flows, increases with distance. It can thus be expected that labor-market related pull factor coefficients change, and become more significant, with distance (labor migration). In contrast, we expect that pull factors that reflect local amenities are most important to people who move over shorter distances (residential migration). The share of migrants that are motivated by these factors in the aggregate flows should decrease with distance; coefficients should thus become less significant with distance.

The above framework allows us to identify more accurately the impact of residential-migration related and labor-migration related variables. However, rather than using a “threshold” distance (d^*), we prefer to use a more flexible model. We therefore re-write Equation (5) as follows:

Model 4

$$m_{ij} = \exp\left\{\alpha_0 + \theta_i + \eta_j + \sum_{k=1}^{K} \alpha_{1,k} \ln x_{i,k} + \sum_{h=1}^{H} (\pi_{0,h} + \pi_{1,h} \ln d_{ij}) \ln x_{j,h} + \sum_{h=1}^{H} (\mu_{0,h} + \mu_{1,h} \ln d_{ij}) \ln \tilde{x}_{j,h} + \beta_{ij} \ln d_{ij} \right\} + \varepsilon_{ij} \qquad (8)$$

When $\hat{\pi}_1$ and/or $\hat{\mu}_1$ turn out to be statistically significant, this provides evidence of a changing relative importance of pull factors at destination *j* and/or in neighboring destinations *j*' over distance.

If the coefficient $\hat{\pi}_1$ associated with, say, employment growth is positive, this would mean that the attractiveness of (favorable) local labor-market conditions at destination *j*, inducing labor migration, increases with distance. Conversely, if the coefficient $\hat{\pi}_1$ associated with local amenities is negative, this would mean that the attractiveness of amenities at destination *j*, inducing residential migration, decreases with distance. In other words, the composition of the migrations flows (i.e., in terms of labor versus residential migrants) may change with increasing distance.

4. Estimation

4.1 Problem of under-determinacy

Given that the number of unknown parameters in the Models 2 through 4 is larger than the number of observations, these models are under-determined or "ill-posed". Therefore, we cannot use classical estimation techniques. Hence, we use the Generalized Cross-Entropy (GCE) method (e.g., Golan et al., 1996).

A major advantage of GCE is that it allows for estimating unit-specific coefficients even within a cross-section framework. In other words, we do not need to resort to a panel-data framework.

4.2 Generalized Cross-Entropy

To implement the GCE method, the problem of estimating the parameters of the Poisson gravity model has to be converted into a constrained optimization problem.

Reparameterization

The implementation of GCE requires that the parameters of the model are specified as linear combinations of some predetermined, discrete support values and unknown probabilities (weights). Then, the estimation problem is converted into a constrained minimization problem, where the objective function, specified in Equation (7) below, consists of the joint cross entropy. This objective function is to be maximized, subject to the appropriate data-consistency, normalization, and (possibly) other constraints.

We show the operations of GCE for Model 3. This model can be re-parameterized in terms of a set of unknown probability vectors $\mathbf{p}_\alpha, \mathbf{p}_\beta, \mathbf{p}_\theta, \mathbf{p}_\eta$, and $\mathbf{p}_\varepsilon$ (of dimension $M \geq 2$), where $\mathbf{p}_\alpha = (p_1^\alpha, \ldots, p_M^\alpha)'$, and so on, and support vectors $\mathbf{s}_\alpha$, $\mathbf{s}_\beta$, $\mathbf{s}_\theta$, $\mathbf{s}_\eta$, and $\mathbf{s}_\varepsilon$, where $\mathbf{s}_\alpha = (s_1^\alpha, \ldots, s_M^\alpha)'$, and so on. The parameters α, β, θ, and η and the error term ε can then be written as linear combinations of the probabilities and the associated support values as $\alpha_0 = \mathbf{p}'_{\alpha_0}\mathbf{s}_\alpha$, $\beta_{ij} = \mathbf{p}'_{\beta_{ij}}\mathbf{s}_\beta$, $\theta_i = \mathbf{p}'_{\theta_i}\mathbf{s}_\theta$, and so on.

Optimization problem

After appropriate re-parameterization, the complete GCE optimization problem for the gravity model can be formulated as follows:

<cross-entropy criterion>

$$
\begin{aligned}
\underset{\mathbf{p}}{\text{Min}}\, CE = {} & \mathbf{p}'_{\alpha_0} \ln\left(\frac{\mathbf{p}_{\alpha_0}}{\mathbf{q}_{\alpha_0}}\right) + \sum_{k=1}^{K} \mathbf{p}'_{\alpha_1,k} \ln\left(\frac{\mathbf{p}_{\alpha_1,k}}{\mathbf{q}_{\alpha_1,k}}\right) \\
& + \sum_{h=1}^{H} \mathbf{p}'_{\alpha_{2,},h} \ln\left(\frac{\mathbf{p}_{\alpha_2,k}}{\mathbf{q}_{\alpha_2,k}}\right) + \sum_{h=1}^{H} \mathbf{p}'_{\alpha_{3,},h} \ln\left(\frac{\mathbf{p}_{\alpha_3,k}}{\mathbf{q}_{\alpha_3,k}}\right) \\
& + \sum_{i=1}^{N} \mathbf{p}'_{\theta_i} \ln\left(\frac{\mathbf{p}_{\theta_i}}{\mathbf{q}_{\theta_i}}\right) + \sum_{j=1}^{N} \mathbf{p}'_{\eta_j} \ln\left(\frac{\mathbf{p}_{\eta_j}}{\mathbf{q}_{\eta_j}}\right) + \sum_{i=1}^{N}\sum_{j=1}^{N} \mathbf{p}'_{\beta_{ij}} \ln\left(\frac{\mathbf{p}_{\beta_{ij}}}{\mathbf{q}_{\beta_{ij}}}\right) \\
& + \sum_{i=1}^{N}\sum_{j=1}^{N} \mathbf{p}'_{\varepsilon_{ij}} \ln\left(\frac{\mathbf{p}_{\varepsilon_{ij}}}{\mathbf{q}_{\varepsilon_{ij}}}\right)
\end{aligned}
\tag{7}
$$

subject to

<data-consistency constraints>

$$
\begin{aligned}
m_{ij} = \exp\Big\{ & \mathbf{p}'_{\alpha_0}\mathbf{s}_\alpha + \sum_{k=1}^{K} (\mathbf{p}'_{\alpha_{1,k}}\mathbf{s}_\alpha)\ln x_{i,k} + \sum_{h=1}^{H} (\mathbf{p}'_{\alpha_{2,k}}\mathbf{s}_\alpha)\ln x_{j,h} \\
& + \sum_{h=1}^{H} (\mathbf{p}'_{\alpha_{3,k}}\mathbf{s}_\alpha)\ln \tilde{x}_{j,h} + \mathbf{p}'_{\theta_i}\mathbf{s}_\theta + \mathbf{p}'_{\eta_j}\mathbf{s}_\eta + (\mathbf{p}'_{\beta_{ij}}\mathbf{s}_\beta)\ln d_{ij} \Big\} + \mathbf{p}'_{\varepsilon_{ij}}\mathbf{s}_\varepsilon
\end{aligned}
\tag{8}
$$

<mean-preservation constraints>

$$
\sum_{i=1}^{N} \mathbf{p}'_{\theta_i}\mathbf{s}_\theta = 0\,; \quad \sum_{j=1}^{N} \mathbf{p}'_{\eta_j}\mathbf{s}_\eta = 0 \tag{9}
$$

<adding-up (normalization) constraints>

$$
\begin{aligned}
& \sum_{m=1}^{M} p_m^{\alpha_0} = 1\,; \quad \sum_{m=1}^{M} p_m^{\alpha_{1,k}} = 1\,; \quad \sum_{m=1}^{M} p_m^{\alpha_{2,h}} = 1\,; \quad \sum_{m=1}^{M} p_m^{\alpha_{3,h}} = 1\,; \\
& \sum_{m=1}^{M} p_m^{\theta_i} = 1\,; \quad \sum_{m=1}^{M} p_m^{\eta_j} = 1\,; \quad \sum_{m=1}^{M} p_m^{\beta_{ij}} = 1\,; \quad \sum_{m=1}^{M} p_m^{\varepsilon_{ij}} = 1
\end{aligned}
\tag{10}
$$

The principle of minimum cross-entropy means that we are choosing, given the data-consistency and other constraints, the estimates of the unknown probability vectors **p** that can be discriminated from the prior probability vectors **q** with a minimum of difference (Golan et al., 1996, p. 11). In other words, we are looking for the "least informative" probability distributions that are consistent with the data- and other constraints, and the prior information reflected in the support ranges and the prior probabilities.

After solving the entropy optimization problem in (7)-(10), the parameter estimates and the residual terms can be recovered as $\hat{\alpha}_0 = \hat{\mathbf{p}}'_{\alpha_0}\mathbf{s}_\alpha$, and so on. Hence, for **Model 3** a total of 1,990 = 1[α_0] + 3 [$\alpha_{1,k}$] + 3[$\alpha_{2,k}$] + 3[$\alpha_{3,k}$] + 44[θ_i] + 44[η_j] + 44×43[β_{ij}] parameters are estimated with only 1,892 observations on M_{ij}.

Support ranges

Since there are no specific bounds on the parameters, one *common* support vector ($M = 2$) for all the parameters is set as $\mathbf{s} = (-100, 100)'$, which represents a range wide enough to include all possible outcomes (see also, e.g., Golan et al., 2001). The supports for the error term are defined as $\mathbf{s}_{\varepsilon} = (-10\sigma, 10\sigma)'$, where $\sigma = 137.6$ is the empirical standard deviation of gross migration (i.e., the dependent variable in the gravity model). Applying the usual "three-sigma" rule (Pukelsheim, 1994) leads to infeasibility of the optimization problem, probably due to the "over-dispersion" or "extra-Poisson variation" of the dependent variable (i.e., the variance many times exceeds the mean).

In addition, we use prior information about the unknown probability vectors **p** in the form of informative priors and non-informative (uniform) priors. In particular, for the coefficients associated with the covariates we set $\mathbf{q} = [q_1, q_2]' = [1-\hat{\alpha}, \hat{\alpha}]'$ (informative priors), where $\hat{\alpha}$ are the corresponding OLS estimates (reported in table 1). For the unobserved origin-destination effects and the error terms we set $\mathbf{q} = [0.5, 0.5]'$ (uninformative priors). The choice of the informative priors is motivated on the ground that the OLS estimates can be viewed as "defensible" initial hypotheses with respect to the magnitudes of the corresponding coefficients.

As the GCE formulation results is a form of shrinkage estimator (Golan et al., 1996, p. 31), a larger weight will be assigned to the terms in the cross-entropy objective associated with the smallest of the prior probabilities. As a result, the probabilities associated with the unknown parameters will be "shrunk" faster toward the priors (or, deviations from the priors will be penalized).

5. Empirical application

Gross migration flows, over the period 1998-2003, and distances between the 44 municipalities of the Belgian province of Limburg. We only consider *internal* (i.e., intra-provincial) migration. A map of the (location of the) municipalities is given in Fig. A1 in the Appendix. A map of the geographical aggregate net in-migration rates (expressed as percentages of total population) is given in Fig 1.

Fig. 1

6.1 Data and variable description

We use a simple Poisson gravity model, where the dependent variable is gross out-migration from origins *i* to destinations *j*, m_{ij}, over the period 1998-2003. Our geographic units are the 44 municipalities of the province of Limburg in Belgium.[2] The variance (stdev = 137.6) of the dependent variable is much larger than the mean (= 58.3), hence there is *over-dispersion* or "*extra Poisson variation*" (229 zeros = 12.1%; 599 cases smaller than 5 = 31.7%; median = 11.5).

Although a model for migration would ideally include *all* variables that affect migration, this obviously is (practically) impossible. The model we want to develop should, however, make clear how employment opportunities, on the one hand, and the supply of amenities and housing availability, on the other hand affect migration. Specifically, our model includes only a few explanatory variables (i.e., push and pull factors). The definitions of these variables, along with some summary statistics, are presented in table 2 (more information is given in table A1 in the Appendix).

Push factors

The included variables (push factors) at origins are: population density, educational attainment of the working population, and the proportion of "non-Belgian population".

POPULATION DENSITY – This variable (log) is used as a proxy for housing availability (e.g., vacancy rate in the housing stock, rent levels, diversity of choice in size and location, and quality) and congestion effects, 1991.

EDUCATION – This variable is defined as the percentage of the working population with higher ("tertiary") education, 1991 (most recent data).

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[2] It should be noted that municipalities are not "self-contained" units, since there is appreciable inter-municipal (workplace-residence) *commuting*. As a result, the units considered in this analysis do not jointly identify both residence and job location (Mueser and Graves, 1995, p. 187). In other words, place of residence and job location may be different (are not necessarily in the same municipality).

NON-BELGIAN POPULATION – This variable is defined as the percentage of the total population coded as non-Belgians (originating from Turkey, Italy, Spain, Morocco, Greece, and "other countries"), 2000.

Pull factors

The included variables at destinations are employment growth, amenities (measured by the Herfindahl index), and income growth.

EMPLOYMENT GROWTH – We use the growth of (salaried) employment as a measure of job availability (e.g., job openings), 1998-2001. Agglomeration economies can also play a role in job search. Since there are diverse job types and numerous workers with various skills and knowledge in larger urban centers, jobs and workers tend to match more easily there. Local employment growth would seem to be an obvious pull factor for labor migration. But, here a problem of endogeneity may potentially arise. However, we treat this variable as an exogenous "shifter" of migration.

INCOME GROWTH – Ideally, we should include some indicator of housing prices or housing availability/quality. However, data limitations prevent us from using such indicators. Therefore, we use the growth of taxable income per capita, 1991-1998, as a proxy for the (in-) availability of affordable housing. Migration in the province of Limburg may also imply a selective "migration of incomes". Hence, the local growth of (taxable) incomes per capita may also be considered as a pull factor. Specifically, it can be assumed that neighboring income (growth) also counts as an amenity, capturing the variety of ways in which income influences the quality of life in an area (e.g., Brueckner et al., 1999). For example, the presence of excellent restaurants (a major amenity) in a particular neighborhood may be partly due to the high incomes (growth of incomes) of the local residents.

AMENITIES – The diversity of the local economy is measured by the (log) Herfindahl index of industrial concentration, and is used here as a proxy for local *amenities*, 1998 (e.g., Brueckner et al., 1999; Mueser and Graves, 1995). Local supply of amenities is also a pull factor for residential migration. The Herfindahl index can be interpreted as an indicator of the diversity of the local economies, and is used here as a proxy for local *amenities* (i.e., the provision of demand or consumption externalities), which are usually difficult to quantify as such.[3] Cleary, such location-specific amenities may strongly affect the attractiveness of certain municipalities for (a particular category of) people to reside. On the other hand, preferences for open space, natural amenities, residential property, and "small-town values" may also attract people. In other words, there may exist a tension between two opposing forces, which can be avoided if people live in rural-urban neighborhoods and frequent to the nearby (amenity-rich) urban centers. Recall that the value of the Herfindahl index is *inversely* related to the diversity of the local economy,[4] and is defined as

$$H = \sum_{q=1}^{Q} s_q^2 \quad (1/Q \le H \le 1) \tag{10}$$

The inverse of the Herfindahl index, $1/H$, is an indicator of the diversity of the local economy (the higher the value of $1/H$, the more diverse is the local economy). There are agglomeration economies (economies of "variety") on the consumption side. Consumers can choose more suitable goods and services from a larger variety in larger urban centers, and enjoy the "city light" effects there as well.

Distance

Perhaps the most important deterrent to migration is distance. It has been suggested that distance measures transportation and psychic costs of migration as well as availability of information (e.g., Greenwood, 1975). In a small region such as the province of Limburg, large differences in short- versus long-distance costs are very unlikely. Also, transportation costs are small compared to other costs associated with relocation. The psychic costs of a distant move can constitute of being far from one's relatives and friends (social network). Finally, before moving people are likely to want information about, say, the housing market in the location of destination in order to obtain housing. In the case of labor migration, they may also need information about the labor market in order to get a new job. Some information may be costly to acquire for more distant regions (no "face-to-face" exchange of information, with

[3] By "amenities" we mean a myriad of public and private services, such as administration, education, health care, shops, restaurants, entertainment, recreation, and the like. These features generate *demand* externalities, since they can be supplied only if there is a sufficient scale of demand.

[4] Using a hierarchy-index (measuring the spheres of influences of urban centers), produced by Van Hecke (1998), did not produce satisfying results.

relatives and friends, on job availabilities and characteristics). Therefore, psychic costs and availability thus seem the most important contributors to distance deterrence in the province of Limburg.

For a residential migrant, distance will deter in a different way than for a labor migrant. A residential migrant does not (is supposed not to) change of job. This implies that the new residence must be at an acceptable commuting distance from his or her job location. Thus, it can be expected that the distance deterrence to residential migrants is closely connected with deterrence to commuting distances.

Distance may be measured in a number of ways. Here, distance (log) is measured as the Euclidean distance, based on the coordinates of the centroids for each municipality. The resulting distances in the municipality-level migration system ranges from 62.2 kilometers (between Hamont-Achel and Gingelom) to only 2.2 kilometers (between Neerpelt and Overpelt). Migration is generally assumed to decrease with distance because it increases the generalized costs of moving, or because it reduces the amount of information about destinations available to potential migrants. However, it is unrealistic to assume an homogeneous distance-deterrence effect.

The spatial structure of the aerial units may also introduce bias. Contiguous municipalities are likely to experience more migration than those which do not have a common boundary, simply because there will be more short-distance moves that happen to cross the boundary. Similarly, municipalities that are elongated rather than compact are liable to have more short-distance, cross-border migrants. Similar ideas are demonstrated by Boyle and Flowerdew (1997), among others. Rather than using alternative measures of distance, such as the distance between "migration-weighted centroids", we assume non-homogeneity of the distance-deterrence effect. For two reasons: firstly, data limitations (migration data for the various zones within each municipality are not available); secondly, using alternative distance measures would still assume a single (homogeneous) distance-deterrence parameter.

Table 2

Unobserved (unmeasured) factors

Since it is incredible that the (small number of) included explanatory variables can account for all cross-sectional heterogeneity, the problem of omitted-variable bias may arise.

Therefore, we "correct" for unobserved origin/destination heterogeneity in a way which is somehow similar to including origin/destination-specific dummies.

6.2 Estimation results

We show the estimation results for **Model 1** (OLS) and **Model 2** through **Model 4** (GCE) in table 3. For estimation, we used *TSP* (OLS) and *GAMS* (GCE).

Estimated coefficients

Our primary interest is in the estimates obtained from **Model 3** (GCE). All the estimated coefficients have the expected sign.

Migrants are pushed by population density (rising housing prices, congestion,…). Furthermore, educational status of the working population at origins is a driving force for out-migration, and this finding is in line with prior expectations. We also find a push effect from the proportion of the non-Belgian population at origins. However, it is not straightforward to give an explanation for this finding. Who are those migrants from the municipalities with a high proportion of non-Belgians? Are they Belgian migrants trying to "escape" from these particular municipalities (residential migration) or are they non-Belgians searching for better job opportunities in other municipalities (labor migration)?

Migrants are pulled by the local supply of service-based amenities (*AMENITY*, measured by the Herfindahl index) as well as by local labor-market conditions (*GR_EMPLOY*) in the municipalities of destination. It is instructive to compare these results with the estimated coefficients associated with the spatially lagged pull factors (*LAG_AMENITY* and *LAG_GR_EMPLOY*). In terms of the role of local amenities, we find evidence for scenario 3 (see table 1); that is, the existence of localized demand externalities tends to lead to agglomeration. People would move to destinations where service-based amenities are (urban centers), but equally well to destinations that are close to urban centers (rural-urban fringe areas). It should be noted that the spatial-lag effect of amenities is stronger (larger in absolute value), which provide evidence of a moderated, migration-driven pattern of urban sprawl. The same can be said about the presence of local job opportunities.

Interestingly, scenario 2 seems to be emerging from the estimated coefficients associated with the income-growth variable. Income growth in particular destinations seems to "divert" migration to neighboring destinations.

Finally, as expected, distance has a negative effect on migration. The distance-deterrence elasticity is, *on average*, –1.379, with a standard deviation of 0.208. This shows that there is substantial spatial heterogeneity (i.e., ranging from –2.052 to –0.269). In other words, there is no homogeneous distance-deterrence effect. Overall, the distance-decay deterrence effect is fairly elastic: the distance decay elasticity is greater than 1, in absolute value, in 92.7% of the cases (1,753 cases out of a total of 1,892). The average distance between the municipalities involved for $\left|\hat{\beta}_{ij}\right| > 1$ is 28.5 km (weighted average is 16.5 km); the average distance for $\left|\hat{\beta}_{ij}\right| < 1$ is 9.5 km (weighted average is 8.7 km). A kernel density plot showing the estimated distribution of the distance-decay elasticities is presented in Fig. 3.[5] Furthermore, we find a U-shaped relationship between distance-decay elasticity and distance, as shown in Fig. 4:

$$\hat{\beta}_{ij} = -0.80367 - 0.03831 d_{ij} + 0.00052 d_{ij}^2 + \hat{e}_{ij}$$

$$\text{Pseudo } R^2 = 0.436 \qquad n = 1892$$

The distance is somewhat less elastic for shorter- and longer-distance movements, with the critical distance (at the maximum distance-deterrence effect) being equal to 36.8 km. This U-shaped relationship may also be related to a shift in the composition of aggregate migration from residential migration (free choice?) to labor migration (necessity?).

Fig. 3

Fig. 4

A map of the variability of the distance deterrence effect, for the example of Hasselt, is presented in Fig. 5. Clearly, the distance elasticity is smaller for short-distances moves to or from surrounding municipalities (one remarkable exception is Kinrooi).

Fig. 5

This results demonstrates that, other things being equal, those people living in a particular place *i* which is close to place *j*, are more likely to migrate to *j* than those living in places which are more distant from place *j*. This results is consistent with empirical evidence in the

[5] The kernel density is calculated using a Gaussian kernel with bandwidth parameter set as in Silverman (1986).

literature, showing that contiguous municipalities are likely to experience more migration than those which do not have a common boundary, simply because there will be more short-distance moves that happen to cross the boundary. Similarly, municipalities that are elongated rather than compact are liable to have more short-distance, cross-border migrants. Similar ideas are demonstrated by Boyle and Flowerdew (1997), among others.

Relative importance

Given the fact that the explanatory variables are measured on different scales, simple coefficients do not allow comparison of the relative importance of the variables. In order to gauge the relative impacts of the variables on migration, we have calculated the "standardized marginal effects", evaluated at the sample means of the variables.[6]

The calculated standardized marginal effects, which are shown in Fig. 2, suggest that distance plays the most important role in explaining migration patterns. Also, local amenities – particularly those present in neighboring municipalities – and population density appear to be of appreciable importance. On the other hand, local employment growth plays only a relatively minor role.

Table 3

Unobserved push/pull effects

By including unobserved heterogeneity, substantial changes in (several) estimated coefficients can be observed (see also Simonsohn, 2006, p. 6). So, there are reasons to suspect that unobserved heterogeneity is also driving migration.

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[6] Let $Y = e^{\alpha+\beta X}$, $y^* = (Y - \overline{Y})/\sigma_Y$, and $x^* = (X - \overline{X})/\sigma_X$, then it can easily be shown that the "standardized marginal effect" of the explanatory variable *X*, evaluated at its sample mean $\overline{X}$ (where $x^* = 0$), is

$$\left.\frac{\partial y^*}{\partial x^*}\right|_{x^*=0} = \hat{\beta}\left(\frac{\sigma_X}{\sigma_Y}\right)\tilde{Y},$$

where $\tilde{Y} = e^{\hat{\alpha}+\hat{\beta}\overline{X}}$.

Fig. 6 shows the geographical distribution of the estimated unobserved push/pull effects. There is no evidence of spatial correlation. For many locations, these effects are to some extent "countering" each other. The net result is shown in the lower panel of Fig. 6.

Fig. 5

Interestingly, these findings can be related to the geographical distribution of public transport infrastructures (not measured); that is, those destinations that are located at close proximity to the main express- highways (bold lines in Fig. 6) and have relatively easy access to the national railway network (dotted lines in Fig. 6) may be able to attract (labor and/or residential) migrants. For example, it may be conceivable that many in-migrants to these municipalities work in (commute to) other locations outside the province of Limburg (e.g., Brussels or Antwerp), where wages are generally known to be higher.

Interaction between pull and distance effects

The results from **Model 4** (GCE) are also in line with prior expectations. The positive values for the estimated π_1 parameters indicate that the pull effect of *AMENITY* (*GR_EMPLOY*) at destinations *j* is decreasing (increasing) with larger migration distances. This provides indirect evidence of the fact that longer-distance movements are more to be associated with labor migration, whereas shorter-distance moves can be associated with residential migration.

The positive impact of distance on the amenity effect in neighboring municipalities (*LAG_AMENITY*) is even stronger. This may be indicative of the existence of some *tension*, in the migration decision, between the service-based amenities associated with urban centers, on the one hand, and the open-space amenities associated with rural-urban or exurban fringe areas (rural-urban sprawl). On the other hand, the pull effect of job opportunities in neighboring municipalities (*LAG_GR_EMPLOY*) seems to slightly decrease with distance.

6. Conclusions and remarks

We used a simple (unconstrained) Poisson gravity model to assess some major determinants of internal migration between the municipalities of the province of Limburg in Belgium. The empirical results show the existence of trade-offs between the constraints imposed by distance, on the one hand, and several push and pull factors, on the other hand.

It has been shown that internal migration in the province of Limburg has been driven – through pulling mechanisms – to a large extent by the localized supply of amenities and job opportunities.

A key finding of the present study is the spatial heterogeneity (variability in distance-decay effects) and the U-shaped relationship between the distance-deterrence effect and the distance. Another interesting finding is that the choices of the migrants are guided by both economic (labor migration) and consumption (residential migration) motives. We also found evidence of existing agglomeration effects – i.e., spatial clustering of receiving municipalities with favorable conditions in terms of amenities and job opportunities. Income growth at destinations plays a deterrent role, and "diverts" migration to neighboring municipalities. Finally, it is striking to see that the net effect of the unobserved factors can be related to the geographical pattern of public transportation infrastructures and facilities.

References

Boyle, P.J. and Flowerdew, R. (1997). “Improving distance estimates between areal units in migration models.” *Geographical Analysis*, 29(2): 93-107.

Brueckner, J.K., Thisse, J.F., and Zenou, Y. (1999). “Why is central Paris rich and downtown Detroit poor? An amenity-based theory.” *European Economic Review*, 43: 91-107.

Carrión-Flores, C. and Irwin, E.G. (2004). Determinants of residential land-use conversion and sprawl at the rural-urban fringe. *American Journal of Agricultural Economics* **86**, 889-904.

Ekamper, P. and Van Wissen, L. (2000). *Regionale arbeidsmarkten, migratie en woon-werkverkeer*. NIDI, Netherlands Interdisciplinary Demographic Institute.

Fotheringham, A.S. and O’Kelly, M.E. (1989). *Spatial Interaction Models: Formulations and Applications*. Kluwer Academic Publishers, Dordrecht.

Fratianni, M. and Kang, H. (2006). “Heterogeneous distance-elasticities in trade gravity models.” *Economics Letters*, 90, 68-71.

Ghatak, S., Levine, P., and Price, S.W. (1996). “Migration theories and evidence: an assessment.” *Journal of Economic Surveys*, 10, 159-198.

Golan, A., Judge, G., and Miller, D. (1996). *Maximum Entropy Econometrics: Robust Estimation with Limited Data Sets*. John Wiley & Sons, New York.

Greene, W.H. (2003). *Econometric Analysis*, 5th edition. Pearson Education, Inc., Upper Saddle River, New Jersey.

Greenwood, M.J. (1975). “Research on internal migration in the United States: a survey.” *Journal of Economic Literature*, 13, 397-433.

Mueser, P.R. and Graves, P.E. (1995). “Examining the role of economic opportunity and amenities in explaining population redistribution.” *Journal of Urban Economics*, 37, 176-200.

Pukelsheim, F. (1994). “The three-sigma rule.” *The American Statistician*, 48, 88-91.

Rey, S.J. and Montouri, B.D. (1999). “U.S. regional income convergence: a spatial econometric perspective.” *Regional Studies*, 33, 143-156.

Sá, C., Florax, R.J.G.M., and Rietveld, P. (2004). “Determinants of the regional demand for higher education in The Netherlands: a gravity model approach.” *Regional Studies*, 38(4), 375-392.

Sen. A. and Smith, T.E. (1995). *Gravity Models of Spatial Interaction Behavior*. Heidelberg: Springer-Verlag.

Shen, J. (1999). “Modelling regional migration in China: estimation and decomposition.” *Environment and Planning A*, 31, 1226-1238.

Shioji, E. (2001). “Composition effect of migration and regional growth in Japan.” *Journal of the Japanese and International Economies,* 15, 29-49.

Silverman, B.W. (1986). *Density Estimation for Statistics and Data Analysis*. New York: Chapman & Hall.

Simonsohn, U. (2006). “New Yorkers commute more everywhere: contrast effects in the field.” *Review of Economics and Statistics*, 88(1), 1-9.

Van Hecke, E. (1998). “Actualisering van de stedelijke hiërarchie in België.” *Tijdschrift van het Gemeentekrediet*, 52(3), No. 205, 45-76.

Vermeulen, W. (2003). Interregional migration in The Netherlands: an aggregate analysis. Mimeo.

Table 1. Four different scenarios

Scenarios	Destination j	Nearby destinations j'
Scenario 1	*Urbanization forces* $\alpha_2 > 0$ attraction	$\alpha_3 < 0$ repulsion
Scenario 2	*Sub-urbanization forces* $\alpha_2 < 0$ repulsion	$\alpha_3 > 0$ attraction
Scenario 3	*Agglomeration forces* $\alpha_2 > 0$ attraction	$\alpha_3 > 0$ attraction
Scenario 4	*Dispersion forces* $\alpha_2 < 0$ repulsion	$\alpha_3 < 0$ repulsion

Table 2. Dependent and explanatory variables with description, summary statistics, and hypothesized direction of effect

Abbreviation	Variable	Description	Mean	Standard deviation	Hypothesized direction of effect
MIGRAT	Migration	Migration flow between origin *i* and destination *j*, cumulated 1998-2003	58.3	137.6	
DISTANCE	Distance	Distance in km between centroids of municipalities *i* and *j*	26.8	12.4	–
POPDENS	Urbanization	Degree of urbanization in municipality *i*, measured as the population density (inhabitants per square km), 2000	0.313	0.143	+
EDUC	Educational attainment	Educational status of the population in municipality *i*, measured as the percentage of the working population with higher (tertiary) education, 1991	0.211	0.030	+
ETHNIC	Non-Belgian population	Proportion of foreign population in municipality *i*, measured as the percentage of the population from foreign origin (excluding Dutch immigrants), 2000	0.030	0.037	?
AMENITY	Amenities	Supply of amenities in municipality *j*, measured by the Herfindahl index of industrial (employment) concentration, 1998*	0.187	0.081	+
GR_INCOME	Per-capita income growth	Growth of (taxable) income per capita in municipality *j*, 1991-1998	0.025	0.003	?
GR_EMPLOY	Employment growth	Growth of (salaried) employment in municipality *j*, 1998-2001	0.025	0.102	+
LAG_AMENITY	Spatial lag of amenities	Spatial lag of supply of amenities in municipality *j*, measured by the Herfindahl index of industrial (employment) concentration, 1998*	0.403	0.066	?
LAG_GR_INCOME	Spatial lag of per-capita income growth	Spatial lag of growth of (taxable) income per capita in municipality *j*, 1991-1998	0.056	0.010	?
LAG_GR_EMPLOY	Spatial lag of employment growth	Spatial lag of growth of (salaried) employment in municipality *j*, 1998-2001	0.053	0.010	?

* The Herfindahl index of industrial (employment) concentration can be interpreted as an indicator of the diversity of the local economies, and is used here as a proxy for the supply of local amenities (i.e., localized demand or consumption externalities). It should be noted that the Herfindahl index is *inversely* related to the diversity of the local economy: low values of the index indicate large diversity, whereas high values indicate little diversity.

Table 3. OLS and GCE results for Poisson gravity model

	Model 1 OLS	Model 1 GCE	Model 2 GCE	Model 3 GCE	Model 4 GCE
CONSTANT	6.206 (0.893)***	6.115	6.279	6.213	6.392
Characteristics of origins					
POPDENS (1998)	0.826 (0.090)***	0.831	0.542	0.588	0.544
EDUC (1991)	1.168 (0.182)***	1.127	0.800	0.952	0.670
ETHNIC (2000)	0.219 (0.033)***	0.215	0.219	0.243	0.336
Characteristics of destinations					
AMENITY (1998)	-0.936 (0.075)***	-0.907	-0.582	-0.741	$\hat{\pi}_0$ -1.064
					$\hat{\pi}_1$ 0.091
GR_INCOME (1991-1998)	-68.180 (6.560)***	-64.842	-68.155	-68.172	-68.173
GR_EMPLOY (1998-2001)	0.276 (0.240)	0.244	0.500	0.277	$\hat{\pi}_0$ 0.216
					$\hat{\pi}_1$ 0.032
Characteristics of neighboring destinations					
LAG_AMENITY (1998)	-2.882 (0.432)***	-2.909	-1.852	-2.029	$\hat{\mu}_0$ -3.471
					$\hat{\mu}_1$ 0.750
LAG_GR_INCOME (1991-1998)	47.262 (7.188)***	48.806	47.257	47.285	47.238
LAG_GR_EMPLOY (1998-2001)	1.614 (0.605)***	1.622	2.060	1.731	$\hat{\mu}_0$ 1.643
					$\hat{\mu}_1$ -0.015
Distance					
DISTANCE	-1.349 (0.034)***	-1.347			
Mean $\hat{\beta}_{ij}$			-1.375	-1.379	-1.351
Stdev.			0.295	0.208	0.159
Min.			-2.169	-2.052	-2.323
Q1			-1.565	-1.509	-1.442
Q2 (Median)			-1.440	-1.428	-1.369
Q3			-1.240	-1.323	-1.272
Max.			-0.069	-0.269	-0.058
Unobserved factors					
Mean $\hat{\theta}_i$				0.000	0.000
Stdev.				0.352	0.412
Min.				-0.556	-0.676
Q1				-0.280	-0.301
Q2 (Median)				0.008	-0.089
Q3				0.242	0.291
Max.				0.657	0.812
Mean $\hat{\eta}_j$				0.000	0.000
Stdev.				0.517	0.545
Min.				-1.465	-1.593
Q1				-0.217	-0.273
Q2 (Median)				0.017	-0.013
Q3				0.246	0.312
Max.				1.379	1.301
R^2	0.538	0.540			
Pseudo-R^2			0.999	0.999	0.999

Fig. 1

Map of the population 2000 and net in-/out-migration rates 1998-2003 (defined as percentages of population)

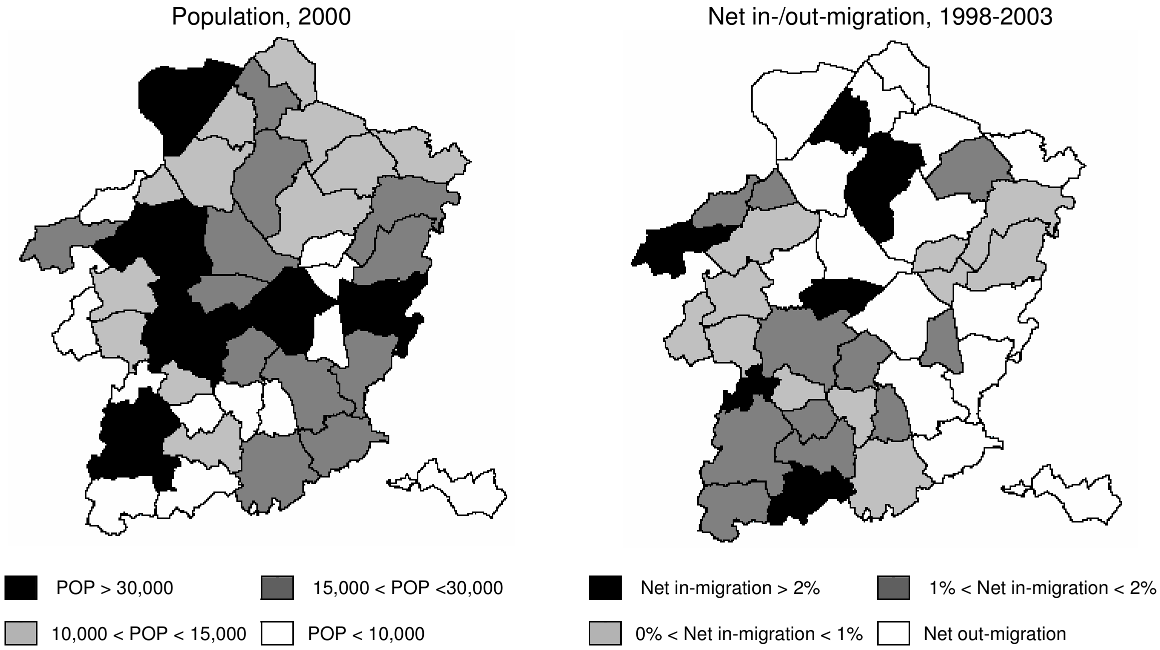


Fig.2
Standardized marginal effects, evaluated at sample means (Model 3)

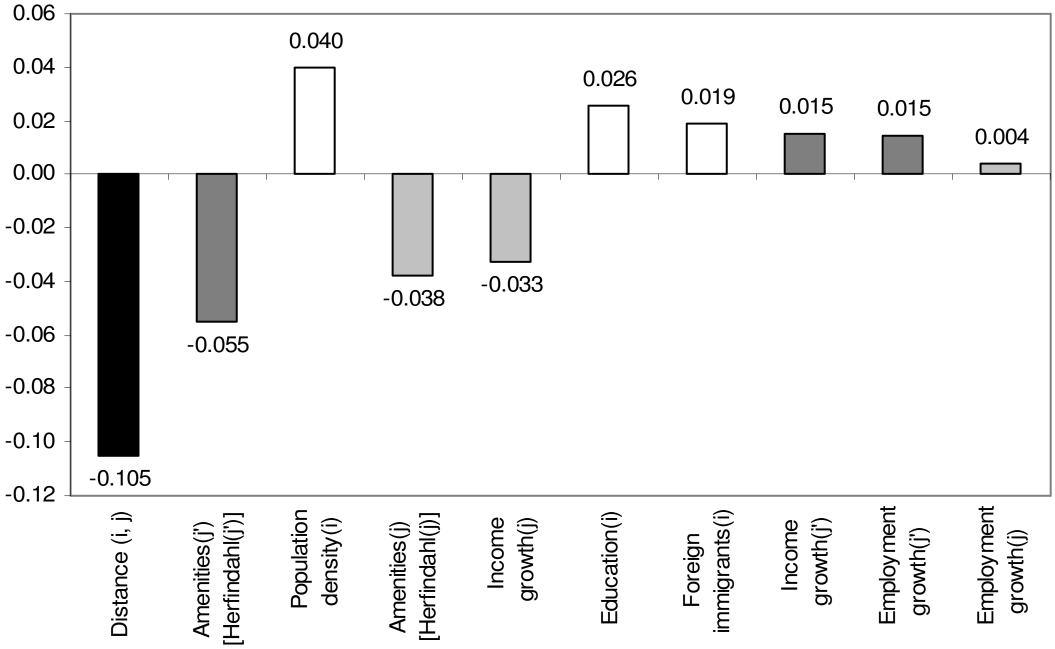


Fig. 3
Kernel density plot of distance elasticities

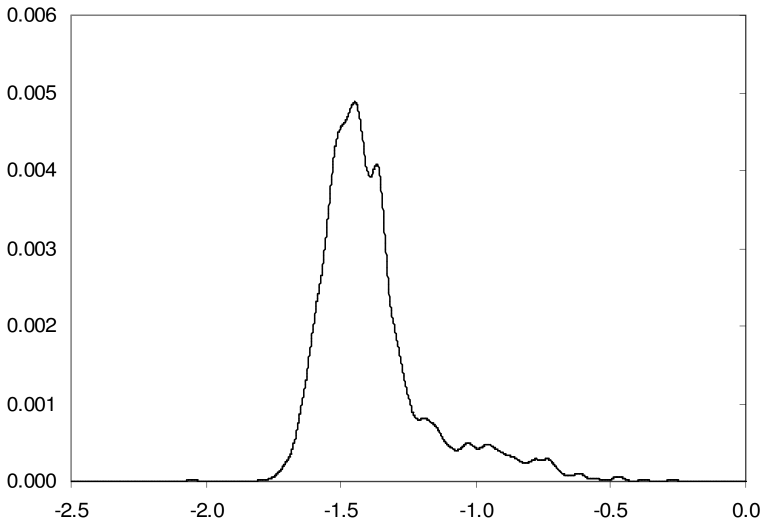


Fig. 4
U-shaped relationship between distance-decay elasticities and distances

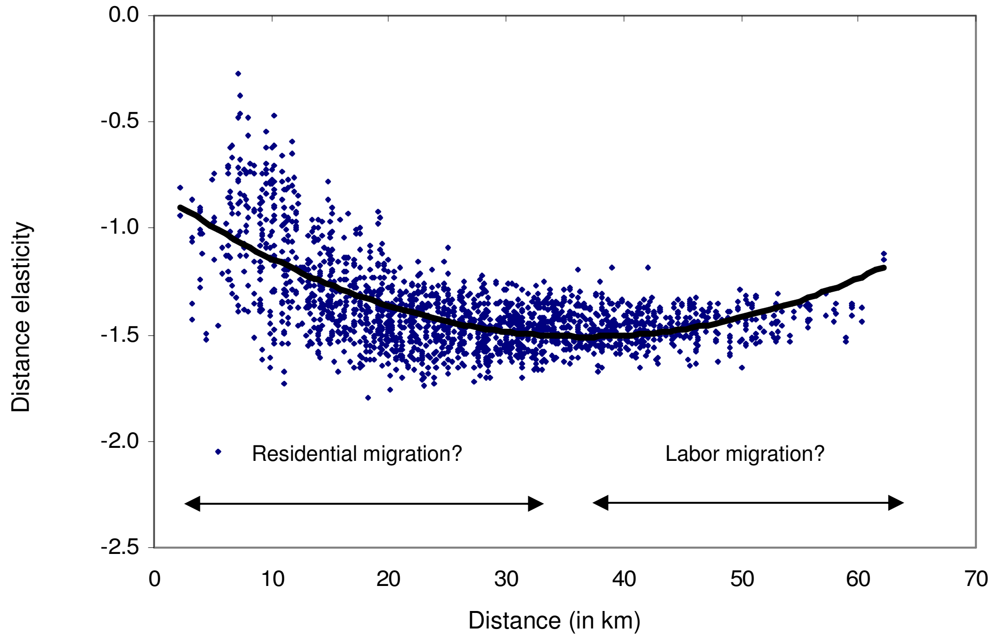


Fig. 5
Maps of heterogeneous distance-decay elasticities (quartiles), example of Hasselt

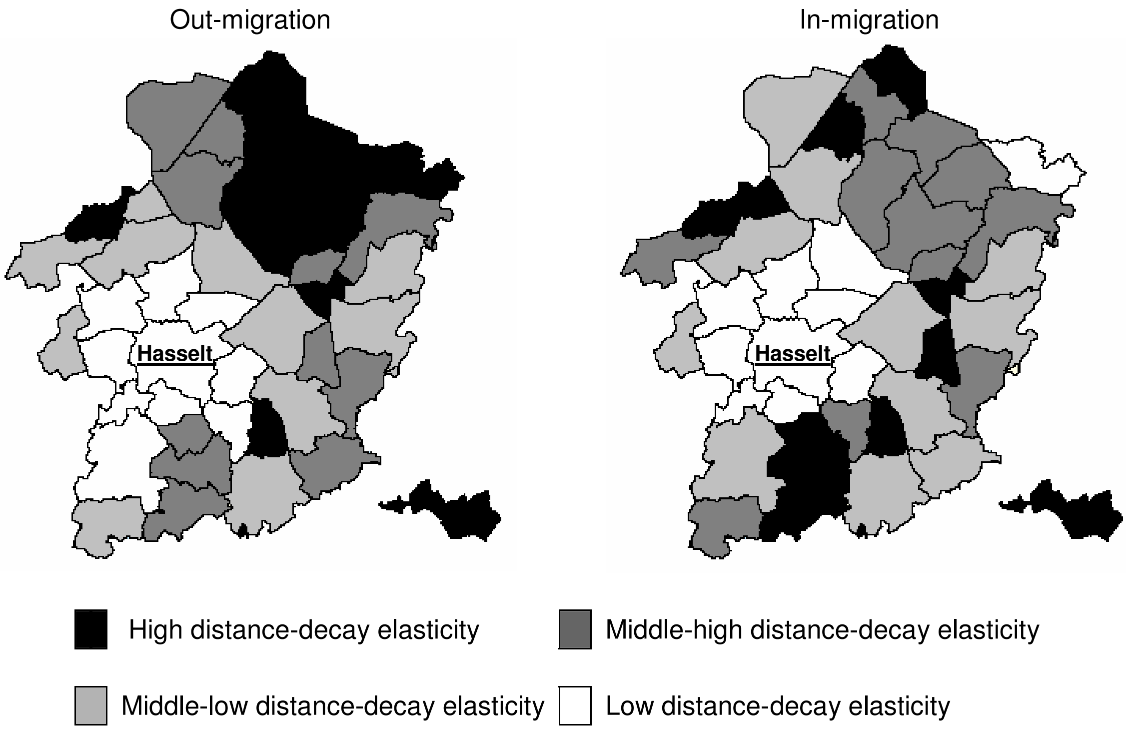
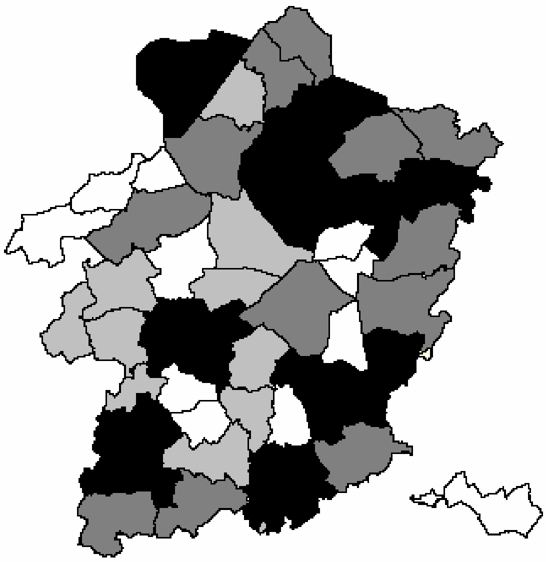
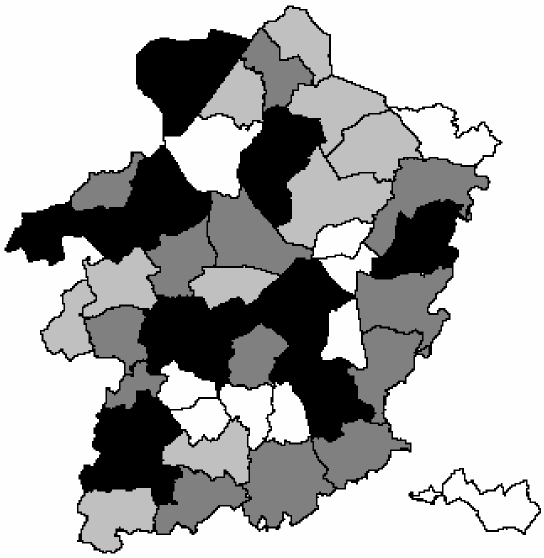


Fig. 6
Maps of unobserved push/pull effects

Unobserved factors affecting *out*-migration ($\hat{\theta}_i$)
[+] pushing (*expulsion* forces)
[–] pulling (*retention* forces)
regardless of included push covariates



Unobserved factors affecting *in*-migration ($\hat{\eta}_j$)
[+] pulling (*attraction* forces)
[–] pushing (*repulsion* forces)
regardless of included pull covariates



Unobserved factors affecting *net in*-migration ($\hat{\eta}_j - \hat{\theta}_j$)
[+] net pulling (*attraction* and/or *retention* forces dominate)
[–] net pushing (*expulsion* and/or *repulsion* forces dominate)
regardless of included push/pull covariates

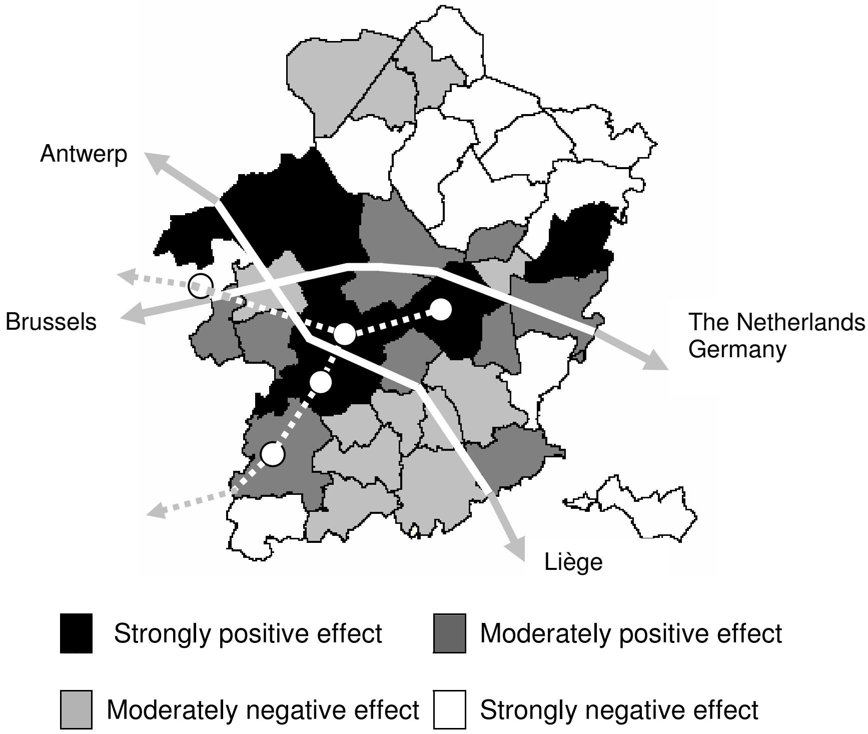


Table A1. Explanatory variables (covariates)

Municipality	Population density (*i*)	Educational attainment (*i*)	Proportion of Non-Belgians (*i*)	-Herfindahl index (*j*)	Growth of income (*j*)	Growth of employment (*j*)	Spat.lagged Herfindahl index (*j*)	Spat.lagged growth of income (*j*)	Spat.lagged growth of employment (*j*)
As	0.326	0.211	0.026	0.108	0.028	0.003	0.460	0.062	0.106
Beringen	0.500	0.212	0.066	0.149	0.027	0.185	0.452	0.061	0.090
Diepenbeek	0.415	0.221	0.015	0.140	0.031	0.154	0.481	0.070	0.018
Genk	0.712	0.221	0.173	0.296	0.031	0.072	0.439	0.065	0.068
Gingelom	0.135	0.168	0.009	0.160	0.026	0.046	0.291	0.040	-0.015
Halen	0.226	0.191	0.010	0.158	0.029	0.006	0.352	0.050	0.010
Hasselt	0.664	0.310	0.030	0.111	0.022	-0.056	0.475	0.069	0.042
Herk-de-Stad	0.269	0.254	0.009	0.133	0.030	-0.125	0.413	0.058	0.053
Leopoldsburg	0.623	0.199	0.038	0.497	0.023	-0.042	0.379	0.053	0.105
Lummen	0.255	0.222	0.014	0.151	0.026	0.143	0.420	0.060	0.039
Nieuwerkerken	0.292	0.188	0.006	0.313	0.030	-0.297	0.366	0.054	0.024
Opglabbeek	0.362	0.201	0.043	0.201	0.023	0.156	0.431	0.060	0.072
Sint-Truiden	0.347	0.219	0.016	0.125	0.024	0.018	0.387	0.052	-0.046
Tessenderlo	0.304	0.226	0.018	0.297	0.026	0.013	0.327	0.044	0.064
Zonhoven	0.485	0.249	0.026	0.148	0.024	-0.082	0.474	0.067	0.089
Zutendaal	0.207	0.259	0.027	0.193	0.030	0.040	0.429	0.063	0.070
Ham	0.281	0.205	0.030	0.258	0.025	0.090	0.401	0.050	0.071
Heusden-Zolder	0.563	0.239	0.090	0.117	0.029	0.185	0.472	0.063	0.089
Bocholt	0.199	0.174	0.012	0.228	0.019	0.023	0.379	0.050	0.108
Bree	0.215	0.243	0.015	0.165	0.020	0.120	0.415	0.053	0.088
Kinrooi	0.212	0.153	0.013	0.124	0.018	0.146	0.317	0.041	0.054
Lommel	0.296	0.196	0.018	0.170	0.023	0.044	0.333	0.042	0.075
Maaseik	0.294	0.214	0.023	0.127	0.019	-0.037	0.307	0.040	0.073
Neerpelt	0.356	0.219	0.013	0.127	0.025	0.140	0.441	0.052	0.104
Overpelt	0.304	0.232	0.012	0.246	0.022	0.088	0.406	0.056	0.132
Peer	0.173	0.207	0.011	0.163	0.026	0.077	0.435	0.056	0.103
Hamont-Achel	0.309	0.161	0.014	0.238	0.023	0.047	0.296	0.039	0.075
Hechtel-Eksel	0.145	0.220	0.019	0.127	0.024	0.075	0.450	0.056	0.091
Houthalen-Helchteren	0.373	0.197	0.127	0.158	0.023	0.050	0.466	0.065	0.072
Meeuwen-Gruitrode	0.137	0.201	0.013	0.228	0.025	0.041	0.428	0.057	0.106
Dilsen-Stokkem	0.274	0.196	0.048	0.324	0.024	-0.010	0.335	0.048	0.076
Alken	0.389	0.241	0.014	0.164	0.029	-0.027	0.514	0.073	-0.021
Bilzen	0.383	0.227	0.018	0.109	0.028	0.080	0.454	0.068	0.033
Borgloon	0.198	0.223	0.012	0.168	0.024	-0.104	0.466	0.065	-0.025
Heers	0.124	0.157	0.009	0.211	0.029	-0.247	0.362	0.050	0.008
Herstappe	0.085	0.243	0.001	0.377	0.023	-0.057	0.308	0.046	0.012
Hoeselt	0.303	0.200	0.015	0.140	0.030	-0.052	0.458	0.069	0.067
Kortessem	0.238	0.234	0.013	0.116	0.029	-0.011	0.530	0.074	-0.013
Lanaken	0.398	0.170	0.020	0.144	0.025	0.063	0.356	0.052	0.049
Riemst	0.270	0.203	0.024	0.140	0.030	-0.033	0.330	0.047	0.044
Tongeren	0.339	0.235	0.016	0.114	0.020	0.132	0.401	0.054	-0.016
Wellen	0.247	0.191	0.010	0.271	0.025	-0.104	0.494	0.076	-0.013
Maasmechelen	0.466	0.172	0.154	0.116	0.026	0.048	0.380	0.052	0.064
Voeren	0.084	0.175	0.020	0.170	0.020	0.087	0.235	0.034	0.023

Fig. A1.
Map of Limburg and its municipalities