A System Dynamics Approach to Model Land-Use/Transport Interactions on the National Level

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1 ABSTRACT

This paper presents an attempt to model domestic migration within Austria. To this end, we slightly adapted the system dynamics land-use/transport interaction (LUTI) model MARS and set up a nation-wide case study. Particular attention was paid to the estimation of the gravity model parameters. Two alternative approaches were implemented: firstly, Poisson regression was applied to derive maximum likelihood estimates. Secondly, the built-in optimizer of the modelling software Vensim was used to estimate parameters by minimizing the sum of squared deviations between observed and predicted migration flows. Both approaches proved practically viable and each one features specific advantages. The optimizer approach obviates the need for external econometric software for parameter estimation; Poisson regression is superior in terms of significance testing for models and individual parameters. Unfortunetaly, despite the fact that both approaches result in satisfactory model fit, the parameter estimates are quite distinct in some cases. Finally, some lines for futher research are indicated.

2 INTRODUCTION

Concern over transport problems, a constant issue in past decades, recently deepened in the context of climate change because of the significant – and ever increasing – transport related CO2 emissions. Policies that aimed to mitigate transport related problems based on measures merely within the transport systems, proved to be inadequate in the past. Consequently, a wider scope of analysis is called for. The notion that transport and land-use are strongly interrelated is accepted common knowledge (Wegener, 2004).

One distinctive feature of this interrelation is that changes within these two systems occur at significantly different speed. Whereas transport users respond relatively fast to changes in the transport system, the land-use system is characterized by a considerable degree of inertia, mainly due to the fact that land-use systems are embodied in physical structures such as buildings and infrastructure. This makes system dynamics modeling a powerful tool in modelling land-use/transport interactions.

The strategic land-use/transport interaction model MARS, developed at the Vienna University of Technology is such a model. To date, it was applied in a series of urban case studies. In order to test and improve the generality of the model, we recently applied the model in a nation-wide case study for Austria.

Due to the wider geographical scope of this case study, model structure had to be adapated, first and foremost to account for the pivotal influence of distance on migration on this spatial level. Furthermore, in connection both with the new model structure and with the new, more comprehensive geographical setting, the model parameters had to be re-estimated.

The rest of this paper is organized as follows: section 3 briefly summarizes observed trends in migration within Austria; section 4 presents the MARS model and its adaptations for the present case study; section 5 outlines the two alternative parameter estimation procedures; the results of the parameter estimation are presented in section 6; finally, section 7 indicates the lines of further research.

3 NATION-WIDE DOMESTIC MIGRATION IN AUSTRIA

This section briefly summarizes migration trends for the years 2002 to 2006, which is the period for which detailed data on migration are available in Austria (Statistik Austria, 2005a).

The most outstanding observation on domestic migration is that migration takes place at fairly short distances. The median distance (air-line) between an old and a new domicile is 12.6 kilometres; for 80% of the migrants the distance is shorter than 24.3 km. Consequently, migration linkages are less quantitatively significant on higher levels of spatial aggregation; as an illustration it may be noted that migration between the districts of Vienna exceeds the flows between all other Austrian provinces.

Urban agglomerations are, by and large, the winners in domestic migration (see Figure 1). With the exception of Salzburg and Bregenz, all provincial capitals, several medium-sized cities and the capital of Vienna experienced population gains in the period. On the contrary, rural districts outside the largest agglomerations tend to experience losses from domestic migration. This includes most inner-alpine districts and districts along the Northern and Southeastern border,

Within the major agglomerations, the most striking trend is an ongoing process of suburbanization. Population shifts from the core cities to surrounding suburban districts affect all major agglomerations. In some cases, including Vienna, this leads to absolute population losses in the core cities; in other cases, overall population gains of the whole agglomeration result in constant or even slightly increasing core city populations (e.g. in the case of the second largest city Graz).

The variations of migration over time reveal no obvious trend and, furthermore, are generally insignificant in quantitative terms. This equally concers the overall volume and the spatial pattern of migration.

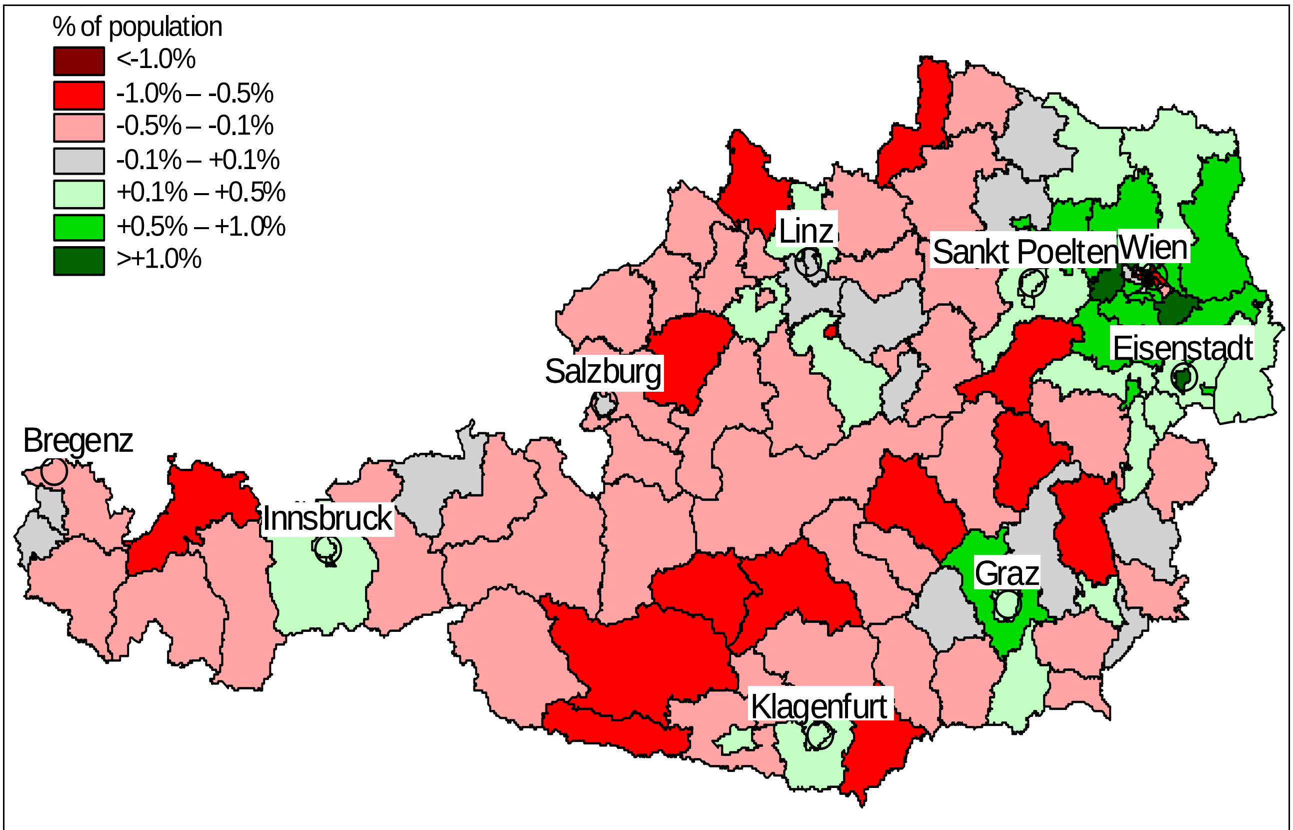


Figure 1 Domestic migration within Austria: average net migration as a percentage of resident population 2002–2005. Source: annual migration statistics of Statistik Austria (2005a, , 2005b, , 2006, , 2007)

4 THE MARS MODEL

4.1 General model description – urban model

The MARS model is a dynamic land-use/transport interaction (LUTI) model. MARS is based on the principles of synergetics (Haken, 1983) and implemented as a systems dynamics model(Sterman, 2000). To date, MARS has been applied to nine European and three Asian cities (see e.g. Pfaffenbichler and Shepherd, 2002). Within the next two years it will be applied also to the cities of Bari in Italy and Porto Alegre in Brazil. A comprehensive model description is given by Pfaffenbichler (2003). The present version of MARS is implemented in Vensim, a widely used system dynamics programming environment.

The MARS model consists of sub models which simulate passenger transport, housing development, household migration and workplace migration; additionally accounting modules calculate assessment indicators and pollutant emissions. The overall structure of the model is shown in Figure 2. The main link between the transport and the location choice model are accessibilities, which are passed on from the transport model to the location choice models, and the spatial distribution of households and employment which are input from the location models to the transport model.

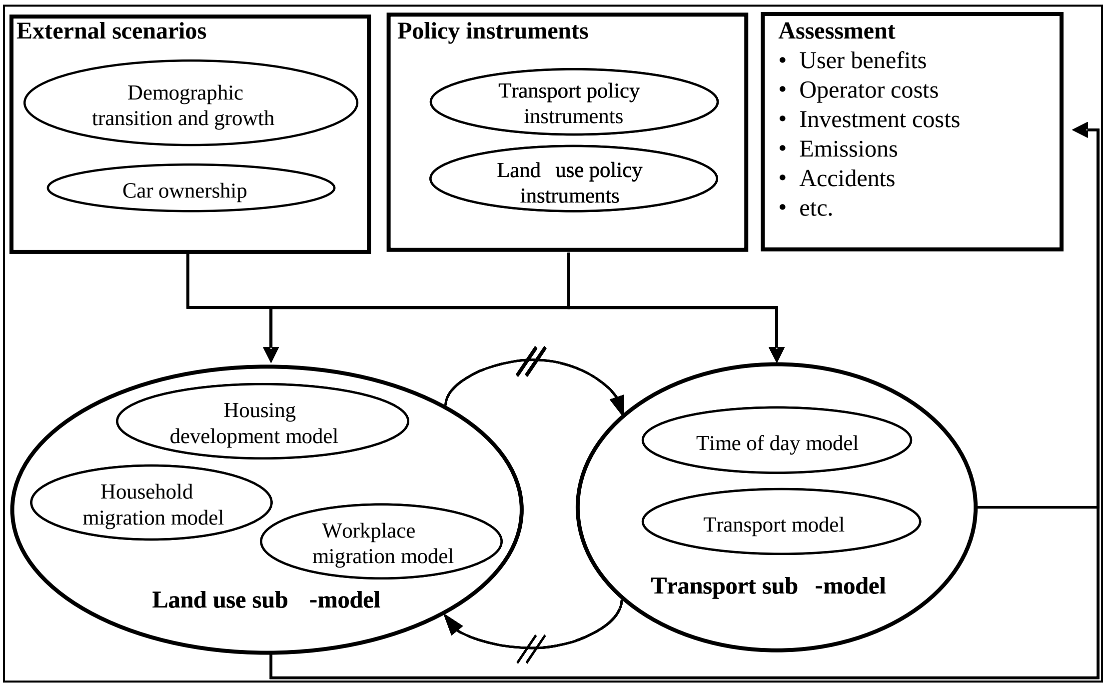


Figure 1 Overall structure of the MARS model

4.2 Structural model adaptations

In the urban MARS model (as described in section 4.1), migration is modelled in a three step approach: first, out-migration per model zone is estimated. The overall out-migration of the whole case study is constrained to a given rate; this rate was usually assumed to be 0.05 per year, equivalent to an average time between two residential moves of 20 years. Second, migrants were pooled over the whole case study. In a third step, the migrants are distributed to destination zones.

Both out-migration, OM_i, and in-migration, IM_j, are modelled based on an exponential function of the form

$$OM_i / IM_j = e^{\alpha_0 + \alpha_1 POP_j + \alpha_2 LR_j + \alpha_2 GL_j + \alpha_3 ACC_j} \quad \text{(for the variables, see Table 1)}$$

The same set of variables was assumed to influence out-migration and in-migration. However, the direction and strength of the link between the explanatory and migration, i.e. the parameters of the model, were different for out- and in-migration. The geographical location of origin and destination zones was not taken into consideration. In other words, the model assumed that the destination choice of migrants was not influenced by the location of their current domicile.

The choice of variables considered (accessibility by car and public transport, level of housing costs and share of recreational green land) was based on several different lines of argument: Firstly, they repeatedly rank among the most important determinants of migration in empirical migration research (ODPM, 2002). Secondly, own empirical studies focussing in particular on Vienna confirmed this importance (Pfaffenbichler, 2003). Third, each of the variables is highly endogenous especially from a land-use transport perspective and in an urban context. As an example, in an urban context the share of green land is both an important cause of migration – in that it constitutes a major amenity perceived be potential migrants – and is simultaneously influenced by migration – as new development can significantly reduce this amenity in urban areas.

An earlier attempt to implement the model without structural changes to Austria revealed the inappropriateness of this structure for a larger spatial scale (Emberger et al., 2007). One major shortcoming was that the observed length distributions of migration were not reflected in the model output: whereas domestic migration in Austria (and elsewhere) is largely short-distance (see section 3), the model predicted significant population shifts from the West to the East of the country, i.e. over a couple of hundred kilometres.

The assumption of unconstrained destination choice was perfectly justifiable given the urban applications of the model. In most cases, the case studies were small enough to make it possible for migrants to maintain

large parts of their "everyday life" (including place of work, social networks, spare time activites, etc.) irrespective of their choice of residence.
To improve on the model we reviewed literature on migration theory (e.g. Greenwood, 1985, Muth, 1971, Bode and Zwing, 1998) and applied migration models (e.g. ODPM, 2002, Flowerdew and Amrhein, 1989, Roy, 2004). Migration theory states that migrants evaluate benefits and costs of migration. Migration related costs include actual costs of migration, the loss of social networks. In most applied work on migration, due to the intangible nature of these effects, distance is taken as a surrogate for the various types of migration costs. Moreover, distance also reflect an information aspect of migration, as people are usually deterred from moving to more distant place they know less about.

In order to account for the overwhelming importance of distance while changing model structure as little as possible, we implemented a two stage migration model: First, the number of out-migrants per zone is estimated following the lines of the existing MARS model. Second, a migration destination choice model distributes the out-migrants (which it takes as an exogeneous input from the out-migration model) over the possible destinations based on characterists of the destinations and the distance between two zones.

The model takes the form of the well-know gravity/spatial interaction model. In general terms, the number of migratants between origin i and destination j, M_{ij}, is modelled as

$$M_{ij} = O_i \frac{exp\left(\alpha_0 + \alpha_1 X_{1,j} + \alpha_2 X_{2,j} + ... + \alpha_n X_{n,j} + \gamma_n Y_{ij}\right) d_{ij}^{\beta}}{\sum_j exp\left(\alpha_0 + \alpha_1 X_{1,j} + \alpha_2 X_{2,j} + ... + \alpha_n X_{n,j} + \gamma_n Y_{ij}\right) d_{ij}^{\beta}}$$

where Oi represents the number of out-migrants of origin i (given exogenously to the distribution model); $X_{1,j} \ldots X_{n,j}$ a set of n attributes relating to destination j with the associated parameters $\alpha_0 \ldots \alpha_n$; Y_{ij} an origin-destination pair specific (dummy) variable with the associated parameter γ; d_{ij} the distance between origin i and destination j.

4.3 The case study setup

The study area comprises the whole territory of Austria; foreign zones are not included at the moment but may be added in later stages to capture cross-border migration in more detail.
The model comprises 121 model zones which are based on the district subdivisions of Austria ('politische Bezirke') plus the 23 municipal districts of Vienna. An attractive feature of the district structure for land-use/transport modelling is that it includes fifteen so-called 'independent cities' (Statutarstädte) which are administratively separated from their hinterland districts. Thus, it is possible to represent core-periphery interactions (such as commuting flows and urban sprawl) for these districts in the model. Moreover, for many statistics, the district level is the most detailed level for which data are available. Finally, the number of districts (121) is a good compromise from a technical point of view in that it keeps calculation time of the system dynamics model within a reasonable limit (which is of particular importance for optimization which usually requires a high number of model runs).

Abbreviation	Variable	Description
Dij	Distance from i to j	Air-line distance between districts i and j
POPj	Population in j	Population of destination j
HRj	Housing rents in j	Housing rents at destination j
ACCj	Accessibility of destination j	Population accessibility potential with a quadratic decay function based on generalized cost between origin and destination
GLj	Share of green land in j	Share of green land as a percentage of total zone area
FUAij	Dummy for same functional urban area	see below

Table 1 Migration variables considered in the model estimations

Two important features of the case study area, and the zoning scheme applied to it, have to be mentioned in this context. Firstly the zones are very heterogeneous amongst each other (highly urbanized areas, and sparsely populated zones). Secondly, the case study area is polycentric and comprises several levels of central places.
However, during the migration model estimation it turned out that the aforementioned core-hinterland relations result in migration patterns that cannot be explained by the variables explaining migration in general. Therefore, we identified "functional urban areas" (FUA) based on patterns of major commuting catchment areas; inter-district relations within the same FUA were singled out in the estimation using a dummy variable.
Names and descriptions of the variables used in the estimated models are given in Table 1.

5 MODEL CALIBRATION APPROACHES

Model calibration is the process of finding estimates for the parameters of a model. A full dataset (explanatory and explained variables) is necessary for parameter estimation. The three main purposes of model estimation are to (i) make quantitative prediction on future development, (ii) to estimate the effects of changes within the system (including changing due to policies) and, finally, (iii) may paramter values themselve deliver insights on a system under investigation (for example on the sensitivity of migration to distance).

Different approaches have been developped to derive parameter estimates based on statistical, econometric and numerical techniques. The most frequently used methods in the case of gravity models are ordinary least squares (OLS) estimation of multiple regression models, maximum likelihood (ML) estimation of Poisson models and neuronal networks (Bergkvist and Westin, 1997). As there is a consensus in the literature on the superiority of ML estimation over OLS estimation, we focus on the former. We do not consider neuronal networks estimation, which usually provide good model fits, on the grounds that they perform rather poor in forecasts and are difficult to interpret in causal terms.

The second estimation approach we consider is motivated by the attempt to carry out model estimation and model runs within the same modelling environment, which streamlines the modelling process and obviates the need for additional estimation software. Vensim offers a built-in optimizing functionality which is perfectly suitable for this purpose.

5.1 Optimization/least squared residual

Vensim has a built-in optimizer functionality which can be used for two purposes (Ventana Systems Inc., 2003): (i) model calibration and (ii) policy optimization.
Basically, the optimizer consists of an algorithm (Powell) which numerically maximizes or minimizes an arbitrary objective function; in Vensim terminology the objective function is called "payoff".
In the calibration mode, the payoff is automatically specified by the software as the sum of the squared deviations between the observed values and the model output for one or more user-specified variables; a weight can be attached to each of the variables. Parameter values are then chosen in an iterative process to minimize payoff. In the policy optimization mode, the payoff can be freely chosen by the modeller.
For the parameter estimation of our gravity model, we chose the calibration mode of the optimizer. Thus, in estimating parameter values, the optimizer (calibration mode) draws on the same criterion of goodness-of-fit as (ordinary) least squared estimation (OLS) in regression analysis. The difference to OLS is that the model need not necessarily be linear in parameters when estimated using the optimizer. The gravity model actually is not linear in parameters; the logarithmic transformation necessary to permit OLS estimation is at the root of some of the problems of OLS estimates for gravity models.
This methodology is a fairly straightforward way to derive estimates of the model parameters. A weakness of the approach is that there are not analytically known measures of model significance. However, through simulation some experimental indications on model and parameter significance can be obtained; moreover, Sterman (1984) suggests the Theil inequality statistics to assess the significance of system dynamic models.
The model structure used in migration parameter estimation is presented in Figure 2.

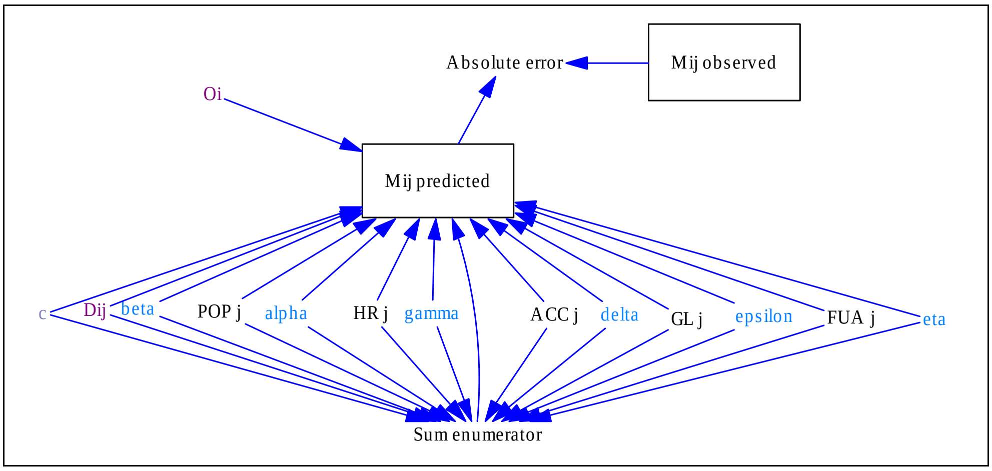


Figure 2 The structure of the model used in parameter estimation

5.2 Poisson model/maximum likelihood estimation

The application of maximum likelihood estimation based on Poisson models to estimate the parameters of gravity model was demonstrated by Flowerdew and Aitkin (1982).

The methodology essentially considers each migrant as a discrete event. It assumes that, firstly, migrants make their choice of destination independently of each other and, secondly, that they are all influenced by the explanatory variable in the same way. Under these assumptions, the number of migrants (count) is Poisson distributed.

Given this theoretical distribution of migrants, the task is to find the parameters of the Poisson distribution that maximize the likelihood of observing an associated set of migration flows. Usually, to facilitate the analysis, the log of the likelihood function is maximized; in the case of the gravity (spatial interaction) model it is given by

$$L^* = \sum_i \sum_j M_{ij} \ln\left(\frac{\overline{M}_{ij}}{\sum_i \sum_j \overline{M}_{ij}} \right)$$

were M_{ij} denotes observed migration flows and $\overline{M}_{ij}$ denotes predicted migration flows between i and j (Fotheringham and O'Kelly, 1989: 51).

One major advantage of Poisson regression over OLS estimation is that it avoids the problems with zero migration flows which may bias OLS parameter estimates if zero flows are frequent. This is typically the case with migration matrices which makes Poisson regression therefore particularly suitable for gravity models of migration.

For maximum likelihood models based on a given theoretical distribution, diagnostic statistics are available which permit to assess the statistical significance of the estimated models.

Poisson regression is implemented in advanced econometric software packages such as R or Eviews. We also attempted to implement the Poisson regression/maximum likelihood estimation directly in Vensim. In principle, this is straightforward to implement by using the optimizer in the policy mode to maximize the analytically know logn-likelihood function (see above).

While were able to obtain numerically equivalent estimates as from the econometrics software used for maximum likelihood estimation, further work is still necessary to calculate the standard errors of the parameter estimates using Vensim. The latter are the basis for deriving diagnostics statistics, which are a major advantage of maximum likelihood estimation over the alternative optimizer approach.

6 COMPARISON OF MODEL ESTIMATIONS

This section presents and compares preliminary results of the model estimation. It covers different model specifications (i.e. different sets of explanatory variables) and the two different estimation approaches outlined in section 5.

The model specifications are limited to the explanatory variables used in the urban MARS models, plus the a model with a (dummy) variable identifying functional urban areas within the case study. This dummy variable turned out to be particularly significant.

6.1 Model fit

The model fit is in general satisfactory. The model specification including only population and distance as explanatory variables yields R^2 values of 0.75 and 0.72 when estimated through minimization of squared residuals and through maximum likelihood, respectively. Adding the three destination-specific explanatory variables used in the urban MARS model (HR, ACC, GL) increases R^2 to 0.86 and 0.78. Further variable were also tested but generally did not notably improve the model fit; for reasons of compatibility with the existing MARS model, they are not included in the migration model for the time being. A significant increase in goodness-of-fit, however, resulted from the inclusion of the "functional urban area" dummy variable which drove R^2 to 0.93 (optimizer, least squares) and 0.86 (maximum likelihood/Poisson regression).

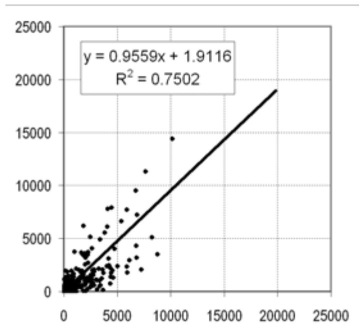
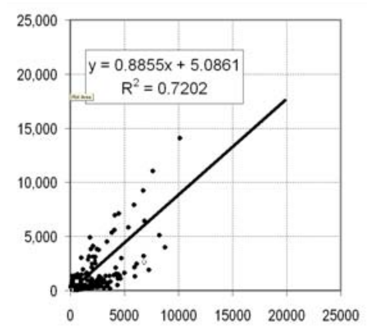
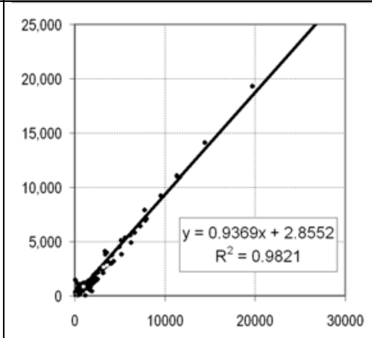
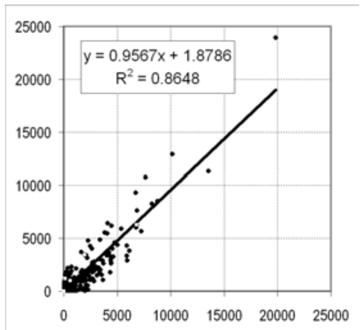
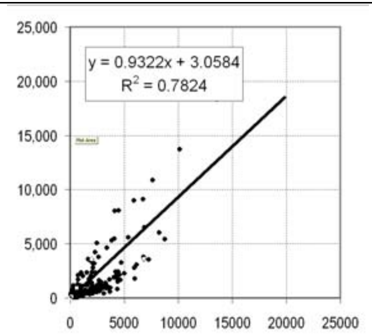
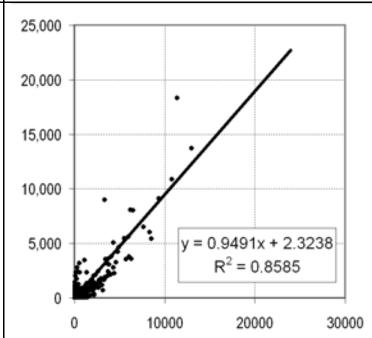
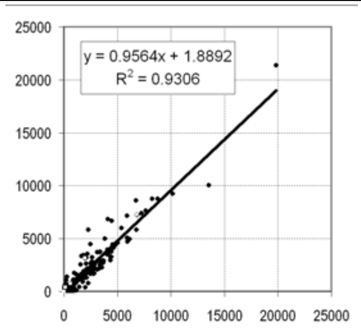
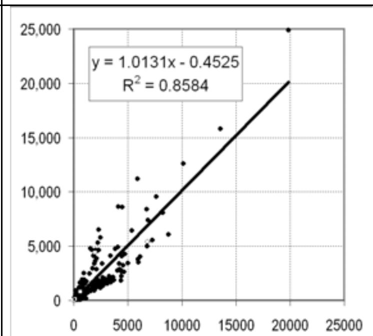
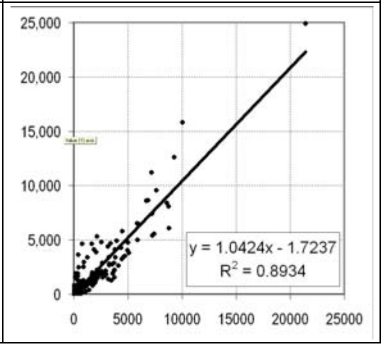
Explanatory variables	**Model estimation** **Optimizer/ least squared residuals (1)**	**Model estimation** **Poisson regression/ maximum likelihood (2)**	**Comparison (optimizer/ maximum likelihood) (3)**
Axis	Horizontal: observed Vertical: predicted	Horizontal: observed Vertical: predicted	Horizontal: optimizer Vertical: Poisson regression
POPj Dij			
POPj HRj ACCj GLj Dij			
POPj HRj ACCj GLj Dij FUAij			

Table 2 Goodness-of-fit of the estimated models: scatterplots of predicted vs. observed migration flows (columns 1 and 2) and comparison of optimizer vs. Poisson estimates (column 3)

Goodness-of-fit measured in terms of R^2 indicates a slight advantage for the parameter estimates from the optimizer/least squares approach; this comes, however, not as a surprise, as R^2 is similar to the objective function (sum of squared residuals) used in the optimizing approach (whereas in Poisson regression, another value, the likelihood of an estimated set of flows, is maximized).

When comparing the predictions from the two estimation approaches (column 3), we could not identify any systematic deviations (e.g. in the sense that one model systematically overestimates distant origin-destination pairs). It is therefore not straightforward to offer explanations for the observed differences in predictions. However, the deviation between the two approaches increases (while at the same time the deviation of each individual approach from data decrease), as the number of explanatory variables increases. This is not very surprising given the rather different absolute values of the parameter estimates.

6.2 Parameter estimates

All parameter estimates are presented in Table 3. As strongly expected, the population parameter (P_j) is positive in all model specifications and with both estimation approaches. Its value is in the range of 0.8 and 1.1 for Poisson regression, while the optimizer varies between 0.2 and 1.8 in the different model specifications. This indicates that the optimizer is more dependent on the model specification.

The parameter on housing rents (HR_j) is negative in all model specifications/with both estimation approaches which is in line with common sense.

The parameter related to accessibility (ACC_j) is negative throughout all model specifications/estimation approaches. This is a frequent finding in empirical models of migration and has been explained in terms of stronger competition between more accessible destinations (which are closer to major population concentrations) and in terms of lack of information on specific destinations in larger population "cluster" on the part of migrants (ODPM, 2002).

Distance between two districts exerts a strong negative influence on migration between these two zones. The parameter values are between -1.8 and -2.0 in the maximum likelihood estimates and between -2.3 and -2.6 in the optimizer estimates. The inclusion of the functional urban area variable notably reduces the absolute value of the distance decay parameter.

(a) Optimizer/least squared residuals estimates

Explanatory variables	POPj			POPj, HRj, ACCj, GLj, Dij			POPj, HRj, ACCj, GLj, Dij, FUAij		
	Parameter	Std. error	Proba-bility (z)	Parameter	Std. error	Proba-bility (z)	Parameter	Std. error	Proba-bility (z)
POPj	0.21	-	-	1.63	-	-	1.78	-	-
HRj	-	-	-	-0.69	-	-	-0.75	-	-
ACCj	-	-	-	-2.27	-	-	-1.41	-	-
GLj	-	-	-	1.31	-	-	-0.56	-	-
Dij	-2.27	-	-	-2.64	-	-	-1.29	-	-
FUAij	-	-	-	-	-	-	2.28	-	-
Constant	0.72	-	-	0.80	-	-	-28.38	-	-
R^2	0.75			0.86			0.93		
SRMSE	4.77			3.28			2.28		

(b) Poisson regression/maximum likelihood estimates

Explanatory variables	POPj			POPj, HRj, ACCj, GLj, Dij			POPj, HRj, ACCj, GLj, Dij, FUAij		
	Parameter	Std. error	Proba-bility (z)	Parameter	Std. error	Proba-bility (z)	Parameter	Std. error	Proba-bility (z)
POPj	0.79	0.00	0.00	1.16	0.00	0.00	0.93	0.00	0.00
HRj	-	-	-	-0.24	0.00	0.00	-0.09	0.00	0.00
ACCj	-	-	-	-0.61	0.00	0.00	-0.41	0.00	0.00
GLj	-	-	-	-0.24	0.01	0.00	-0.38	0.01	0.00
Dij	-1.86	0.00	0.00	-1.95	0.00	0.00	-1.22	0.00	0.00
FUAij	-	-	-	-	-	-	2.01	0.00	0.00
Constant	-0.10	0.04	0.02	8.48	0.03	0.00	5.76	0.04	0.00
R^2	0.69			0.76			0.83		
SRMSE	8.67			4.86			4.28		
Log likelihood	-341098			-278315			-189343		
LR statistic (125 df)	3225657			3351223			3529168		
Probability (LR stat)	0.00			0.00			0.00		

Table 3 Parameter estimates, statistical significance and goodness-of-fit statistics for different model specifications and estimations

The parameter of the functional urban area dummy variable (FUA_{ij}) dummy is positive with both estimation methods. It ranges from 2.0 with maximum likelihood and 2.3 with least squares. This suggests that, migration flows are, ceteris paribus, 7.5 to 10 times more intense if both origin and destination are located in the same functional urban area.

6.3 Summary

It appears that the parameters estimatated by the optimizer (minimizing the sum of squared residuals) yield a slightly better model fit than those from Poisson regression (maximum likelihood) when measured in terms of R^2. However, this result may be biased in favour of the optimizer approach because R^2 is the underlying optimization criterion in this case (whereas in Poisson regression, the likelihood of a predicted set of migration flows is maximized). We will apply additional goodness-of-fit measures to analyze this more in depth.

An advantage of the Poisson regression approach is that it delivers diagnostic statistics to estimate the significance of the calibrated models. This advantage, however, must be put into perspective in the specific case at hand, in which none of the variables we considered proved insignificant.

7 OUTLOOK

Overall, we showed that differnt estimation approaches are applicable to estimate the parameters of gravity models of migration and that they can be easily implemented in modelling environments with an integrated optimizer functionality (in this particular case the Vensim software used for the MARS model). The resulting parameter estimates are insensitive to the software used.

Possible refinements and further research include the following:

One major improvement will be to further refine the migration related data basis. As an example, we intend to use actual road/PT distances instead of air-line distances as currently which is a significant improvement of realism in inner-alpine context.

In methodological terms, we intend to elaborate the maximum likelihood estimation within Vensim, including a fuller set of goodness-of-fit measures and some diagnostic statistics. This has major advantages in practical terms, as model estimation can be carried out faster as it minimizes the need for interfaces between different software packages and obviates the need for dedicated econometrics software, which makes the estimation more readily accessible to a wider range of potential users.

Another priority is a full integration of the migration model and the associated estimation routines with the MARS model. So far, the migration model is implemented as a stand-alone model run independently of the rest of the MARS model with only manual linkages. While this approach greatly facilitated model development and calibration at this early stage, full integration does have its benefits and will therefore constitute the next work step.

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